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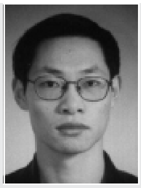

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Artificial intelligence model for water resources management

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The channel network in Pudong New District, Shanghai, is very complex owing to the large area of its basin, its numerous sluice gates, complex influencing factors and some other management issues involving water delivery, flood prevention, floodwater drainage, navigation and saltwater intrusion. It is generally difficult to achieve efficient water resources management merely through manually operating the sluice gates. Therefore, an artificial intelligence modelling system for managing the water resources in the channel network of Pudong New District has been developed by combining hydrodynamic simulation with an artificial intelligence technique. The artificial neural network model is used to develop sluice gate operation procedures according to the water levels in both the outer and inner rivers. The hydrodynamic model is used to simulate the flow discharges and water levels based on the sluice gate operation procedures. This modelling system has been applied successfully to the water resources management of the Pudong channel network. The results indicate that the modelling system satisfactorily meets the demands for sluice gate operation and water resources optimisation management of the channel network and thus provides decision-making support for integrated management of water resources in this inland channel network.

1. INTRODUCTION

Water resources are one of the most important resources for human life and development. The availability of surface water resources depends, to a large extent, on the water quality. A key component in the efficient use of available water resources is the proper management of the existing water resources using advanced technologies. Channel networks are a special type of river pattern which is generally located on alluvial plains, facilitating the exchange of the water within the channel networks with that within adjacent rivers. Since channel networks are usually composed of a number of interconnected branches and the water system is generally very complex, they bring great difficulties for water resources management. The channel network of Pudong New District in Shanghai is an example of this complex water system. Pudong New District is located at the front of the alluvial plain of the Yangtze river delta. The channel network is typical of a tidal channel network. The water exchange between the inner rivers within the channel network and the outer rivers is controlled by sluice gates. Therefore, the channel network is a relatively independent water system. There are 13 sluice gates in this channel network. In order to make full use of these sluice gates for flood prevention, tide blocking, water delivery, floodwater drainage and navigation, the inner river water level needs to be controlled within a reasonable range to ensure the life security of the people and the economic development of Pudong New District. Meanwhile, with a systematic control of the various sluice gates, the water exchange of the inner rivers with the outer rivers can be enhanced to meet the requirements set out by the local government for improving the water quality in the inner rivers. There are 17 main channels in this network, with a total length of 213·3 km and an area of 7·83 km^2. A sketch of the channel network of Pudong New District is shown in Figure 1.

Only a limited number of studies on sluice gate operation have been reported (Chinh *et al.*, 2006; Fan *et al.*, 2007; Li, 1999; Lin and Su, 1996; Loof *et al.*, 2000). Li (1999) presented an empirical method for sluice group operation in tidal rivers. The method is simple, but the operation scheme is possibly not optimal. Lin and Su (1996) developed a model for flood control regarding optimal dispatching of multi-sluice system and the discrete differential dynamic programming linking up with simulation technique was adopted in the model. The application results show that the model is demonstrated and successful, but the calculation process is complicated. Chinh *et al.* (2006) used a genetic algorithm to optimise a gate operation. Most of the sluice gate operation schemes are obtained based on empirical methods or complicated calculation. Thus, there is a need to develop a simpler model for the prediction of sluice gate operation schemes.

For the Pudong channel network, which involves a very large basin area, a number of complex influencing factors should be considered for controlling the sluice gates. Thus it is difficult to achieve efficient management of water resources if the sluice gates are operated only manually. Manual operation has the drawback of relying mainly on operational experience, which is generally less reliable. The volume and rate of water exchange between the inner rivers within the channel network of Pudong New District and the outer rivers (the Yangtze river and Huangpu river) are controlled by the sluice gates, which in turn influence the water quality inside the channel network. Daily operation procedures of the 13 sluice gates were established by the sluice management department from August 2002. The operation of the sluice gates is governed by balancing several requirements, including: flood prevention,

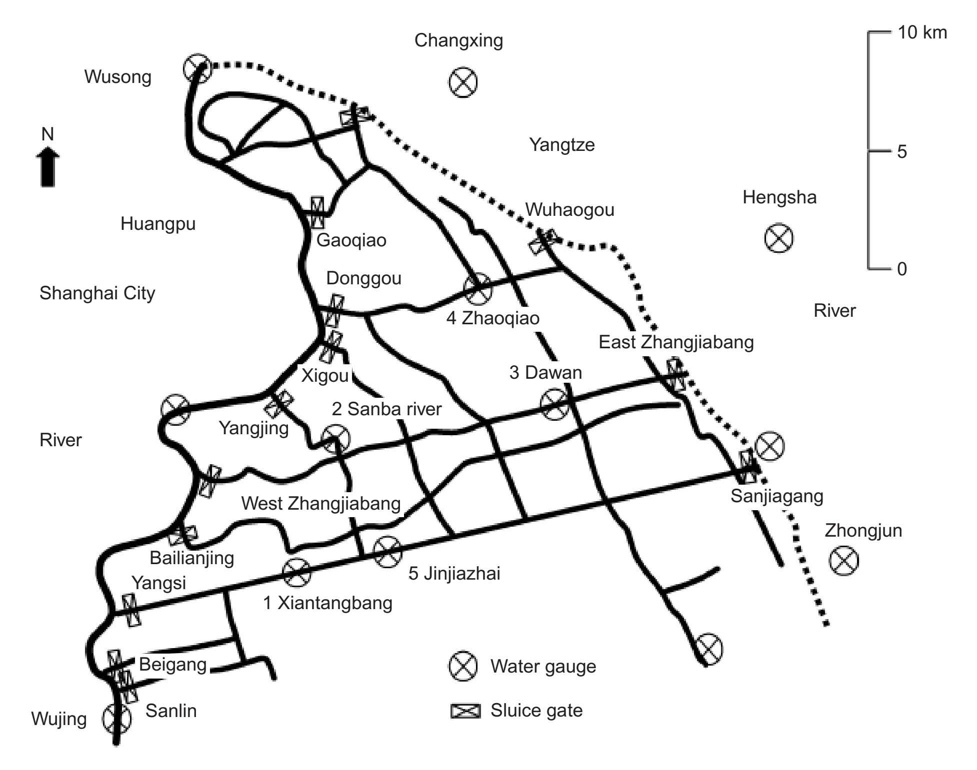

Figure 1. Sketch of the channel network of Pudong New District

floodwater drainage, water level, daily water supply and drainage requirements. However, these requirements cause confusion in operating sluice gates. Furthermore, such an operation scheme is not capable of delivering optimised allocation of the water resources. Therefore, from the point of view of effective water resources management, it will be very beneficial if the operational procedures of the sluice gates are determined intelligently. The main aim of this study was to establish an artificial intelligence modelling system for water resource management to enhance the water resource management efficiency in the channel network of Pudong New District.

Over the past decade, there has been widespread interest in the field of artificial intelligence (ASCE Task Committee, 2000a, 2000b; Jain and Srinivasuls, 2004; Campolo *et al.*, 1999; Lliadis and Maris, 2007). The recent advancements in artificial intelligence technologies are making it possible to solve the intelligent operation of sluice gates. To date, a variety of hydrodynamic models for channel networks are available and the modelling techniques have become quite mature (Aral *et al.*, 1998; Choi and Molinas, 1993; Fread, 1973; Nguyen and Kawano, 1995; Wu *et al.*, 2004). Therefore, technically, the hydrodynamic simulation for channel networks has not been a major problem.

Combining hydrodynamic simulation with an artificial intelligence technique, an integrated modelling system for managing the water resources in the channel network of Pudong New District is proposed in this study. According to the operational principles of the sluice gates, an artificial neural network (ANN) model for sluice gate operation of the channel network has been set up. A hydrodynamic model for channel networks has been established based on numerically solving Saint-Venant equations. The ANN model is used to develop the sluice gate operation procedures according to the water levels in both the outer and inner rivers. The hydrodynamic model is used for the prediction of the water levels and flow discharges based on the sluice gate operation procedures. The results indicate that the artificial intelligence modelling system can be used as a basis for decision making in managing the water resources in the channel network of Pudong New District.

2. ARTIFICIAL INTELLIGENCE MODELLING SYSTEM

The artificial intelligence modelling system developed for managing the water resources in channel networks consists of a database, an ANN sluice gate operation model and a hydrodynamic model. A schematic view of the modelling system is shown in Figure 2. The function of the database obtained by generalising past successful sluice gate operation schemes is used to provide learning samples for training the sluice gate operation model. The trained sluice gate operation model is used to provide the sluice gate operation procedures based on the water levels at both the outer and inner rivers, and the hydrodynamic model is used to simulate the flow within the whole channel network. According to the simulation results, the local water engineers and managers can acquire detailed information on the water levels in the inner rivers, the quantity of water delivery and drainage and so on.

2.1. Hydrodynamic model

2.1.1. Governing equations. The governing equations of unsteady flow in channel networks are the continuity equation and the momentum equation, which are based on the conservation of mass and momentum principles. At the channel junctions, in addition to these equations, two equations for the conservation of mass and energy are needed.

The governing equations for simulating unsteady one-dimension flows in the individual channel segments are known as Saint-Venant equations (Liggett, 1975) and are given as

$$\frac{\partial A}{\partial t} + \frac{\partial \boldsymbol{Q}}{\partial x} - \boldsymbol{q} = 0 \tag{1}$$

$$\frac{\partial \boldsymbol{Q}}{\partial t} + \frac{\partial}{\partial x}\left(\frac{\alpha \boldsymbol{Q}^2}{A}\right) + \boldsymbol{g}A\left(\frac{\partial h}{\partial x} + S_{\mathrm{f}}\right) = 0 \tag{2}$$

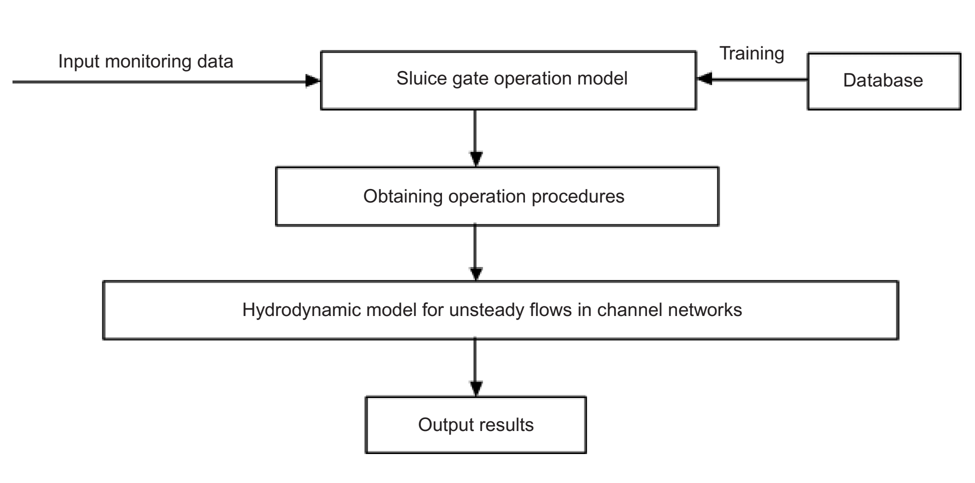

Figure 2. Framework of artificial intelligence modelling system for water resources management in channel networks

where $\boldsymbol{Q}$ is the discharge, h is the water surface elevation above a datum, A is the cross-sectional area, x and t are the spatial and temporal coordinates, $\boldsymbol{q}$ is the side discharge per unit channel length (lateral inflow is positive, lateral outflow is negative), α is the correction factor owing to the non-uniformity of velocity distribution in the cross section, $\boldsymbol{g}$ is the gravitational acceleration and S_{f} is the friction slope. For turbulent flows the friction slope S_{f} can be estimated by using Manning's formula

$$S_{\mathrm{f}} = \frac{n^2 \boldsymbol{Q}|\boldsymbol{Q}|}{A^2 R^{4/3}} \tag{3}$$

where n is the Manning roughness coefficient, R is the hydraulic radius, defined as $R = A/P$, with P being the wetted perimeter.

At a channel junction, assuming no change in storage volume within the junction, the continuity equation can be written as (Yen, 1979)

$$\sum \boldsymbol{Q}_{\mathrm{i}} = \sum \boldsymbol{Q}_{\mathrm{o}} \tag{4}$$

and when the flows in all branches joining at the junction are sub-critical, the equation of energy conservation can be approximated by a kinematic compatibility condition, given as (Akan and Yen, 1981)

$$z_{\mathrm{i}} = z_{\mathrm{o}} \tag{5}$$

In Equations 4 and 5, subscripts i and o stand for the incoming and out-flowing branches respectively.

2.1.2. Solution methods. In the current model, the four-point linear implicit Preissmann finite-difference method (Samuels and Skeels, 1990) is employed for the spatial and temporal discretisations of the equations, while the generalised Newton–Raphson method (Amein and Fang, 1970) is applied to solve the resulting non-linear algebraic equations. The formulations and procedures used for discretising the governing equation are available in many references (Amein and Chu, 1975; Wu *et al.*, 2005; Xu *et al.*, 2001), thus they will not be repeated here.

2.1.3. Treatment of looped channel networks. Channels and their nodes are numbered, while channel junctions are not numbered in the model. Hence there is no need to solve the water levels of junction nodes at the beginning. The numbering of channels starts from main channels, and then branches and finally looped channels. Likewise, the solving process follows such sequence: main channels first, branches second and finally looped channels. The coupling matrix is used to store information about the connection of the channels, branch confluence and channel boundary conditions.

2.1.4. Relaxation algorithm. A relaxation algorithm is used to simulate lateral discharges from branches. Using this algorithm, a complex channel network is treated as a series of individual channel segments, with each channel segment being solved separately. Discharges from other segments are treated as lateral flows by first giving estimated values and then gradually updating these values using an iterative method. Let us take the channel network shown in Figure 3 as an example. First, the flows in the three main channels R1, R2 and R3 are solved. When solving R1, estimated discharges ($\boldsymbol{q}_{\mathrm{ei}}$) that flow into channel R1 from branches R4, R5, R8, R9, R12 and R13 are given. According to $\boldsymbol{q}_{\mathrm{ei}}$ and the upstream and downstream boundary conditions, water level and discharge of each cross-section of channel R1 can be obtained. The water levels at the

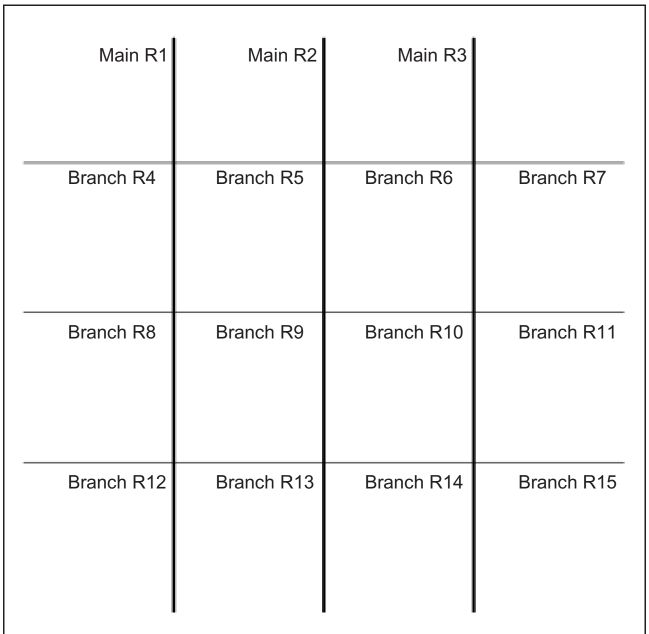

Figure 3. Diagrammatic sketch of looped channel

junctions are then used as downstream boundary conditions for those connected branches. The water levels and velocities in these branches can be obtained based on their corresponding outer boundary conditions. When solving looped channels, water levels at junctions linking with other branches are acted as boundary conditions. Lateral discharges ($\boldsymbol{q}_{\mathrm{ci}}$) flowing into main channels from side branches can then be determined based on the water level differences. New estimated lateral discharges are obtained using

6	$\boldsymbol{q}_{\mathrm{ni}} = \alpha \boldsymbol{q}_{\mathrm{ci}} + (1-\alpha)\boldsymbol{q}_{\mathrm{ei}}$

where α is the relaxation factor ($0 < \alpha \leqslant 1$).

This process is repeated until the convergence condition is satisfied

7	$\lvert \boldsymbol{q}_{\mathrm{ci}} - \boldsymbol{q}_{\mathrm{ei}} \rvert < \varepsilon$

where ε is a permitted error.

2.2. ANN model for sluice gate operation

2.2.1. Artificial neural networks (ANNs). An ANN is a mathematical model based on some features of human brain and nervous system storing and dealing with information. It has an ability to capture a relationship from giving patterns, and hence is suitable for application in the solution of complex problems, such as classification, non-linear modelling, forecasting, fitting, control and identification (Dibike and Solomatlne, 2001; Florentina *et al.*, 1999).

The research of Kolmogorov *et al.* (Zhao, 1999) shows that a continuous function can be represented by a three-layer, feed-forward network. The back-propagation network (BPN) is one of the most popular feed-forward networks in ANNs. The BPN has the advantages of a simple structure, mature algorithm and powerful function, so it becomes a useful technique for solving hydroscience problems. A three-layer BPN consists of an input layer, an output layer and a hidden layer, as shown in Figure 4. In BPN, the input quantities (x_i) are fed into the input layer neurons that, in turn, are passed onto the hidden layer neurons (h_i) after multiplication by connecting to weights (W_{ij}). A hidden layer neuron adds up the weighted input received from each input neuron ($x_{\mathrm{i}}\mathrm{W}_{ij}$) and associates it with a bias (b_j) (i.e. $s_j = \sum x_i \mathrm{W}_{ij} - b_j$). The result (s_j) is then passed on through a non-linear transfer function to produce an output (e.g. sigmoid function; $f(s_j) = 1/(1+\mathrm{e}^{-s_j})$). The output neurons do the same as the hidden neurons. The back-propagation algorithm finds the optimal weights by minimising a predetermined error function (ASCE Task Committee, 2000a). A gradient descent method is often used to modify the network weights. At the

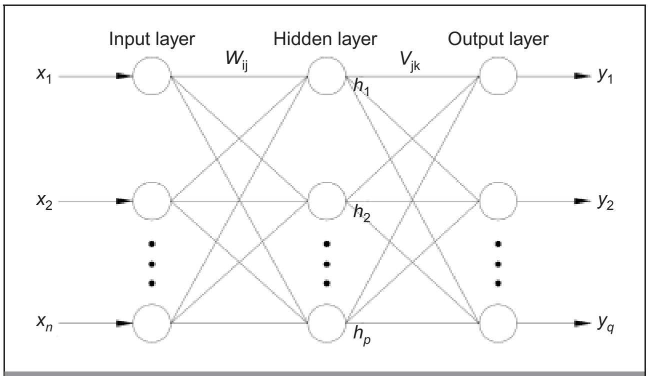

Figure 4. Topological structure of BPN with three layers

beginning of the training, the weights are initialised usually with a set of small random values. Training is stopped when the error is less than a preset value. The details of ANN are available in the literature (ASCE Task Committee, 2000a; Wu *et al.*, 2005).

2.2.2. Establishment of ANN model for sluice gate operation. The main factors that influence sluice gate operation are considered to be the initial water levels of the outer rivers Z_{a}, the average water levels of the outer rivers Z_{b} during water transfer process, the initial inner river water level Z_{s} (set to the average inner river water level before opening sluice gates), the expected inner river water level Z_{t} (the steady inner river water level after closing sluice gates), the widths b and the bottom sill elevations Z_0 of sluice gates. The definition of the average water level of the ith outer river $Z_{\mathrm{b}i}$ is depicted in Figure 5, in which $Z_{\mathrm{b}i}$ is determined using the following equations

8	$$Z_{\mathrm{b}i} = \begin{cases} \dfrac{\int_{T_1}^{T_2} (Z_i - Z_{\mathrm{t}})\mathrm{d}t}{T_2 - T_1} & \text{for water delivery} \\ \dfrac{\int_{T_2}^{T_3} (Z_{\mathrm{t}} - Z_i)\mathrm{d}t}{T_3 - T_2} & \text{for water drainage} \end{cases}$$

where Z_i is the water level of the ith outer river at time t, T_1 and T_2 are the starting and end times when the outer river water level becomes higher than the expected inner river water level and T_3 is the end time that the outer river water level is lower than the expected inner river water level.

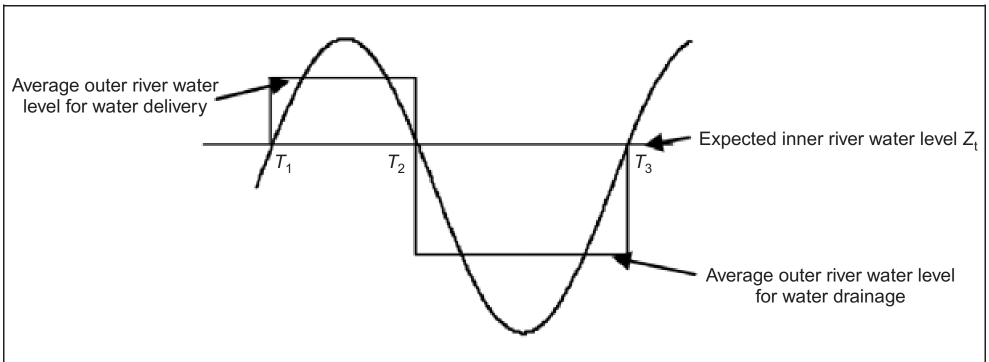

Figure 5. Definition of average outer river water level

The input variables of the operation model are identified as follows: Z_a, Z_b, Z_s, Z_t, b and Z_0. The output variables of the operation model – that is, the sluice gate operation indices – are the opening degree E (the ratio of lifting height to maximum lifting height) and opening time t of the corresponding sluice gates.

Although the sluice gate operation ought to meet various demands, such as for flood prevention, floodwater drainage, running water supply, water quality improvement and navigation, these operation demands are eventually satisfied through controlling the inner river water level. Therefore, the sluice gate operation can be divided into two models. The first type of sluice gate operation model is the water delivery operation model. The objective of water delivery is to maintain inner river water level at a reasonable range, improve water quality in the inner rivers and ensure navigation and supply of domestic water use. Obviously, since the water quality in the Yangtze river estuary is better than that in the HuangPu river, water transferring mostly employs the principle of water delivery from east and water drainage to west in Pudong New District. Therefore the sluice gates used for water delivery are Wuhaogou, East Zhangjiabang and Sanjiagang sluice gates. The input variables of the water delivery operation model are: the initial water levels of the outer rivers corresponding to the three sluice gates Z_{a1}, Z_{a2}, Z_{a3}, the average water levels of the outer rivers corresponding to the three sluice gates Z_{b1}, Z_{b2}, Z_{b3}, the initial inner river water level Z_s, the expected inner river water level after closing the sluice gates Z_t, the sluice widths b_1, b_2, b_3 and the bottom sill elevations Z_{01}, Z_{02}, Z_{03}. The output variables of the operation model are the opening degree E_1, E_2, E_3 and opening time t_1, t_2, t_3 of the three sluice gates. The structure of the water delivery operation model is depicted in Figure 6.

The second sluice gate operation model is the water drainage operation model. The aim of the water drainage operation is to improve the water environment in the inner rivers by controlling sluice gates based on water quality in the inner river, water level, tide and weather conditions, and to meet the needs of flood prevention and floodwater drainage. There are seven water drainage sluice gates used for water drainage: Gaoqiao, Yangsi, Bailianjing, West Zhangjiabang, Yangjing, Xigou and Donggou sluice gates. The input variables of the water delivery operation model are: the initial water levels of the outer rivers corresponding to the seven sluice gates Z_{a1}, Z_{a2}, Z_{a3}, Z_{a4}, Z_{a5}, Z_{a6}, Z_{a7}; the average water levels of the outer rivers corresponding to the seven sluice gates Z_{b1}, Z_{b2}, Z_{b3}, Z_{b4}, Z_{b5}, Z_{b6}, Z_{b7}; the initial inner river water level Z_s; the expected inner river water level after closing the sluice gates Z_t; the sluice widths b_1, b_2, b_3, b_4, b_5, b_6, b_7; and the bottom sill elevations Z_{01}, Z_{02}, Z_{03}, Z_{04}, Z_{05}, Z_{06}, Z_{07}. The output variables of the operation model are the opening degree E_1, E_2, E_3, E_4, E_5, E_6, E_7 and opening time t_1, t_2, t_3, t_4, t_5, t_6, t_7 of the seven sluice gates. The structure of the water drainage operation model is similar to the water delivery operation model, the difference being the number of neurons, so it will not be repeated here.

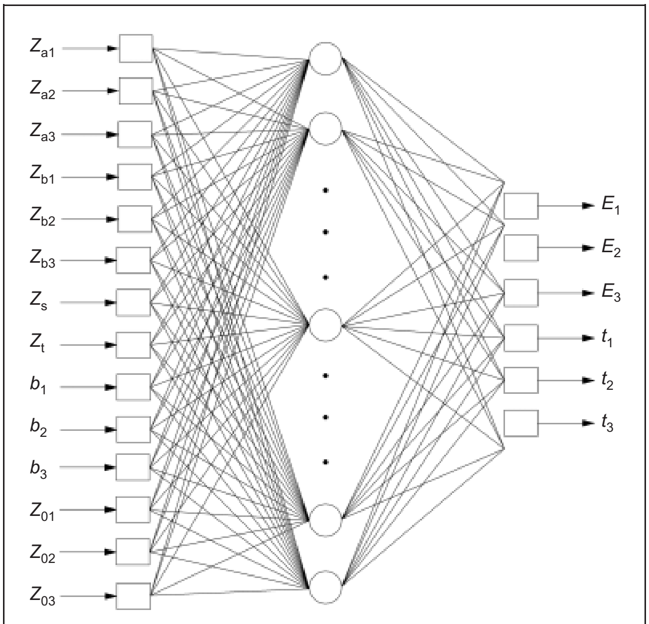

Figure 6. Structure of water delivery operation model

Finally, operation parameter settings in different operation demands should be mentioned. Based on the existing operation schemes, the sluice gate operation models are trained for different operation purposes. When applying the model, the water level in the inner rivers has to be in the range of 2·3 m to 2·6 m in the non-flood season, and 2·6 m to 2·8 m in the flood season respectively. The operation route of sluice gates is shown in Figure 7.

3. MODEL VALIDATION

In order to check the reliability of the artificial intelligence modelling system for water resource management of channel networks presented in this study, the system has been applied to the water transferring experiments in the channel network of Pudong New District. The ANN model of the sluice gate operation was obtained by learning the training samples in the database and then was used to develop an operation procedure for the testing cases. With the established operation procedure, the hydrodynamic model was used to simulate the flow in the channel network and the predicted results were compared with the measured results.

3.1. Prototype water transferring experiment

In this study, a water transferring experiment was carried out in the channel network of Pudong New District. The experimental data were employed to calibrate and validate the hydrodynamic model and the sluice gate operation model.

The experiment was undertaken on 24 September 2003, with the experimental area containing a reach of the Yangtze estuary, Huangpu river and the Pudong river network. Water levels, flow discharges and the opening time and opening degree of the sluice gates were recorded. Data from six gauging stations and ten discharge stations within the Pudong channel network were collected.

3.2. Calibration and validation of hydrodynamic model

The calibration and validation data for the hydrodynamic model comprise the measured water levels from the inner rivers and the total quantity of water delivery and drainage through the sluice gates on 24 September 2003. First, the calibration of the channel roughness and the parameters of the discharge

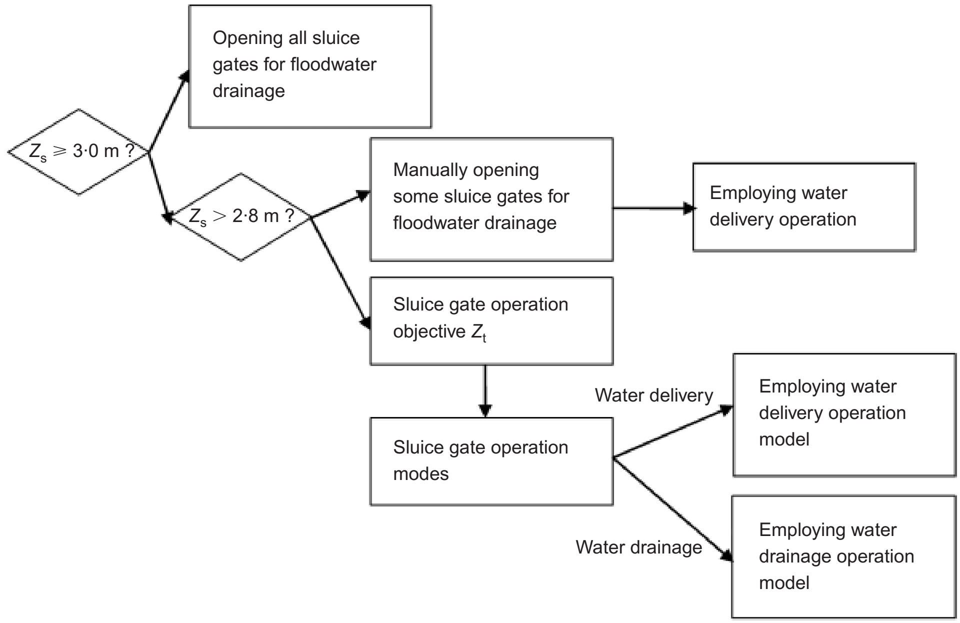

Figure 7. Operation route of sluice gates

formulae of the sluice gates were carried out. The roughness of the channels was determined by comparing the computed and measured water level distributions at the gauging stations in the channel network. Meanwhile, the parameters of the discharge formulae of the sluice gates were obtained by adjusting the computed values of water delivery and drainage to make them close to the measurement values.

3.2.1. Quantity of water delivery and drainage. The validation results for water delivery and drainage are given in Table 1. It shows that the model predicted values for water delivery and drainage agree with the measurements, with the relative error being generally less than 10%.

3.2.2. Water levels at gauging stations. There are six gauging stations in the channel network, shown in Figure 1, located at Xiantangbang, Shijiazhai, Jinjiazhai, Sanba rivers of the Luoshan road, Dawan and Zhaoqiao. Figure 8 shows a comparison between the measured and predicted water levels at the six stations. The model predicted water level distributions fit generally well with the measurements, with the maximum deviation being 0·1 m.

The validation results show that the hydrodynamic model has relatively high accuracy and can be used to simulate the flow and the water quantity of water delivery and drainage in the channel network of Pudong New District.

3.3. Training and validation of sluice gate operation model

3.3.1. Training of sluice gate operation model. In developing BPN models, the sigmoid function was used as the activation function at both hidden and output layers, and the popular back-propagation algorithm (Wang *et al.*, 2000) was employed to train the network. All of the variables are standardised by

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}\alpha + \beta \qquad (9)$$

Sluice	Quantity of water delivery and drainage		
	Measured value: $10^4 m^3$	Calculated value: $10^4 m^3$	Relative error: %
Sanjiagang	114·6	103·4	−9·8
East Zhangjiabang	112·3	102·1	−9·1
Wuhaogou	31·8	29·3	−7·9
Gaoqiao	20·8	18·8	−9·6
Yangsi	58·5	52·1	−10·9
Bailianjing	67·5	67·7	0·3
West Zhangjiabang	46·8	50·8	8·5
Yangjing	49·7	46·7	−6·0
Xigou	49·0	53·8	9·8
Donggou	70·2	63·5	−9·5

Table 1. Comparison between predicted and measured water delivery and drainage values

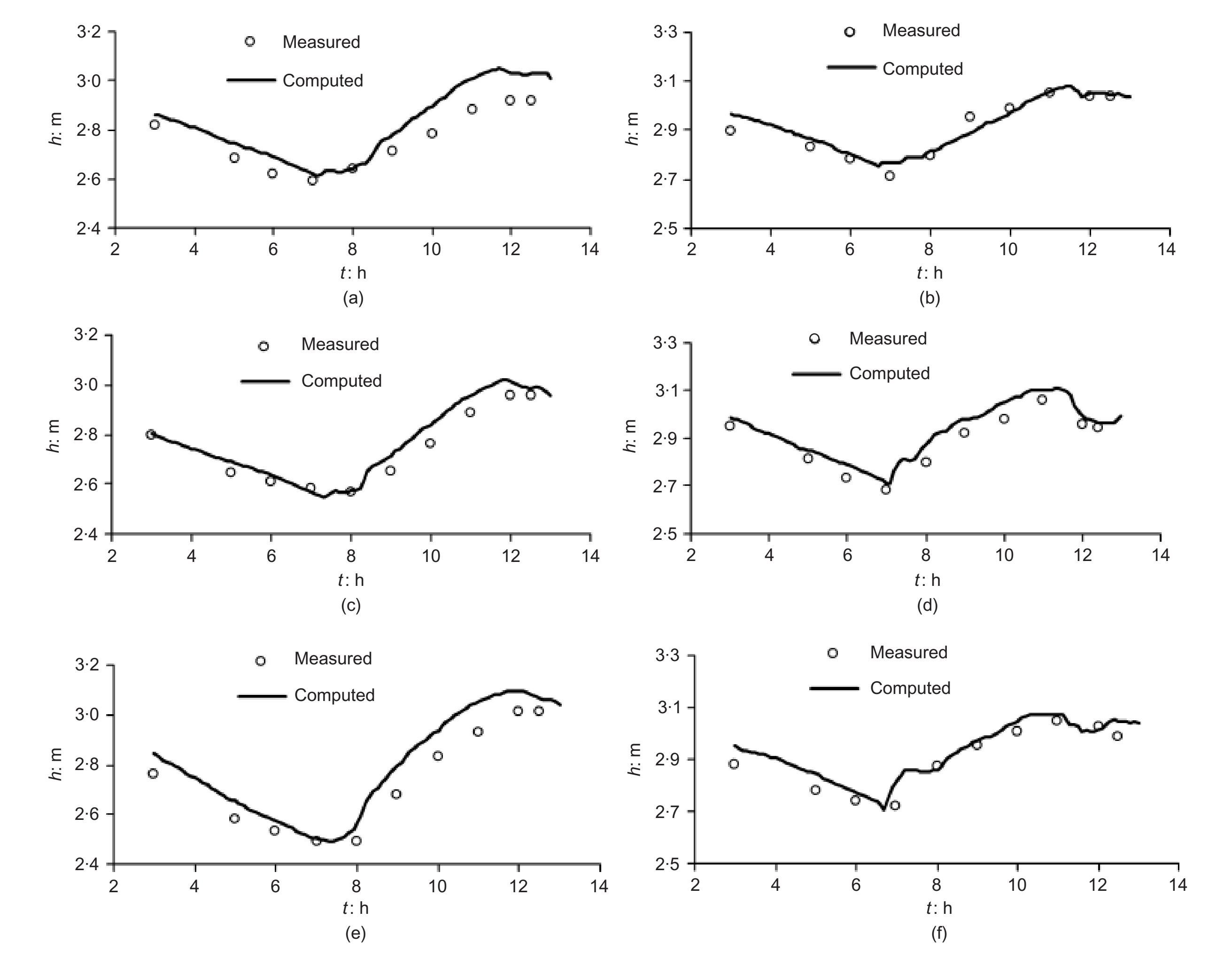

Figure 8. Comparison of measured and simulated water level distributions at: (a) Jinjiazhai station; (b) Zhaoqiao station; (c) Xiantangbang station; (d) Shijiazhai station; (e) Sanba river station; (f) Dawan station

where x' is the standardised variable; $x_{\min}$ is the minimum value in the data set; $x_{\max}$ is the maximum value in the data set; x is the original variable; α is a parameter between 0 and 1, here α is set to 0·9; and $\beta = (1 - \alpha)/2$. In order to determine the number of neurons in the hidden layer, a trial-and-error procedure was used. The number of neurons in the hidden layer was varied from 1 to 20, and for each value of the number of hidden neurons, the BPA was used to minimise the total error at the output layer. Previous successful sluice gate operations for water delivery and drainage were used as learning samples. The number of the training samples used was 230 for the water delivery operation, and 200 for the water drainage operation (Tang *et al.*, 2004). The optimum number of hidden neurons was found to be 4 and 3 for water delivery and drainage operation, respectively. Therefore, the architectures of 14–4–6 and 30–3–14 were found to be the best to capture the input–output relationships inherent in the data under consideration for water delivery and drainage operation respectively. Figure 9 shows the measured opening data against the corresponding ANN-predicted output data at the ending of training. As can be seen, the two ANN models both successfully predicted the measured data. In order objectively to evaluate the model performance, the most commonly employed error measures, such as the root-mean-square error (RMSE) and the coefficient of determination (R^2) were calculated for Figure 9. The RMSE and R^2 are defined as

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{l}\left(\boldsymbol{q}_{\mathrm{m}_i} - \boldsymbol{q}_{\mathrm{p}_i}\right)^2}{l}} \tag{10}$$

$$R^2 = \frac{\sum_{i=1}^{l}\left(\boldsymbol{q}_{\mathrm{m}_i} - \overline{\boldsymbol{q}}_{\mathrm{m}}\right)\left(\boldsymbol{q}_{\mathrm{p}_i} - \overline{\boldsymbol{q}}_{\mathrm{p}}\right)}{\sqrt{\sum_{i=1}^{l}\left(\boldsymbol{q}_{\mathrm{m}_i} - \overline{\boldsymbol{q}}_{\mathrm{m}}\right)^2}\sqrt{\sum_{i=1}^{l}\left(\boldsymbol{q}_{\mathrm{p}_i} - \overline{\boldsymbol{q}}_{\mathrm{p}}\right)^2}} \tag{11}$$

$$\boldsymbol{q} = \sum_{i=1}^{n} \boldsymbol{q}_i = \sum_{i=1}^{n} E_i^{0\cdot5} t_i \tag{12}$$

where $\boldsymbol{q}_{\mathrm{m}}$ is the measured value of $\boldsymbol{q}$, $\overline{\boldsymbol{q}}_{\mathrm{m}}$ is the measured mean value of $\boldsymbol{q}$, $\boldsymbol{q}_{\mathrm{p}}$ is the predicted value of $\boldsymbol{q}$, $\overline{\boldsymbol{q}}_{\mathrm{p}}$ is the predicted mean value of $\boldsymbol{q}$, l is the total number of sample and n is the number of operation sluice gates. For Figure 9(a), RMSE and R^2 are computed as equal to 0·457 h and 0·990, respectively; for Figure 9(b), RMSE and R^2 are, respectively, computed as equal to 1·101 h, and 0·992, implying the successful training of the ANN model.

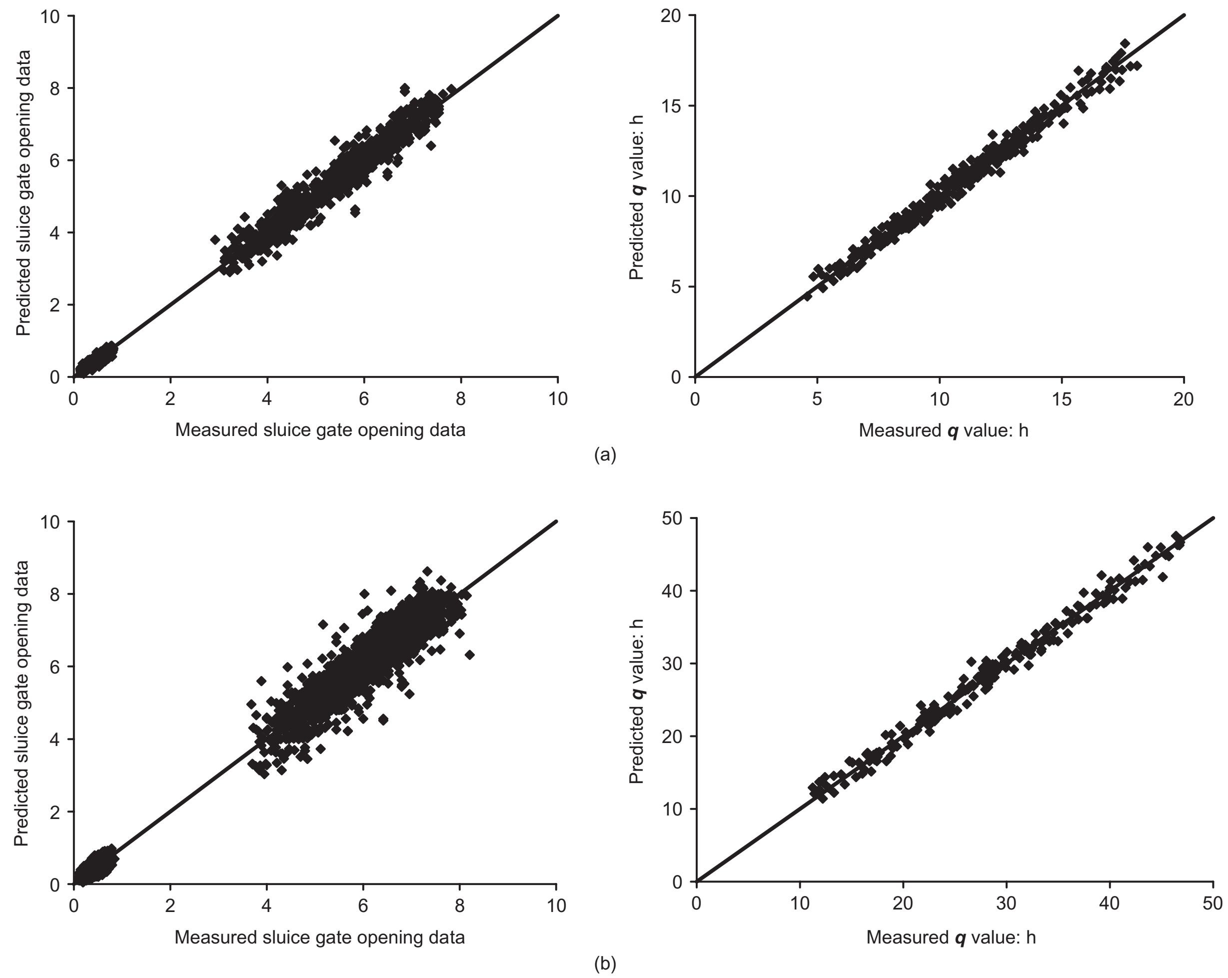

Figure 9. Measured against predicted data at training stage for (a) water delivery operation model and (b) water drainage operation model

3.3.2. Validation of sluice gate operation model. The trained ANN model is validated using the data from the water transferring experiment and database. The number of the testing samples used was 100 for the water delivery operation (including a set of water transferring experiment data and 99 sets of existing data from database), and 96 for the water drainage operation (including a set of water transferring experiment data and 95 sets of existing data from database). Comparison of predicted and measured values is shown in Figure 10. The values of RMSE $= 0{\cdot}560$ h, $R^2 = 0{\cdot}982$ for water delivery operation model and RMSE $= 1{\cdot}335$ h, $R^2 = 0{\cdot}987$ for the water drainage operation model imply a satisfactory performance of the developed ANN model. For the water transferring experiment, the predicted results of the operation indices of the sluice gates for the water delivery and drainage operation schemes are shown in Table 2 and Figure 11 respectively. For the water delivery, the expected inner river water level is 2·748 m, while the predicted value is 2·735 m; for the water drainage, the expected and predicted inner river water levels are 2·261 m and 2·291 m respectively. It is shown that the model largely meets the expected demands. It is clear that when the acquired operation database meets the operation demands, the operation model can give a reasonable operation scheme. With such an operation scheme, the expected inner river water level can be achieved.

4. APPLICATION

An information-based system has been developed for managing the channel network in Pudong New District (Figure 12 and Figure 13). The system comprises primarily three components: a geographic information system (GIS)-based platform for managing and displaying data and model parameter control, a numerical model for hydrodynamic simulation; and an ANN for sluice gate operation control. A real information-based management system for the sluice gate operation has been realised. It is practically significant to the establishment of the information-based system for the implementation of the integrated management strategy of safety, resource and environment in Pudong New District. In the next section, two cases are shown to illustrate the applicability of the artificial intelligence modelling system.

4.1. Case 1: intelligence operation during water transferring experiments

Currently the operation of the sluice gates depends mainly on experience, and it has the shortcomings of a long time and a great difference between the inner river water level after water transferring and the expected inner water level. The artificial intelligence modelling system developed above can be used to overcome the shortcomings and it has been applied to the water transferring experiments during 19–21 September 2004

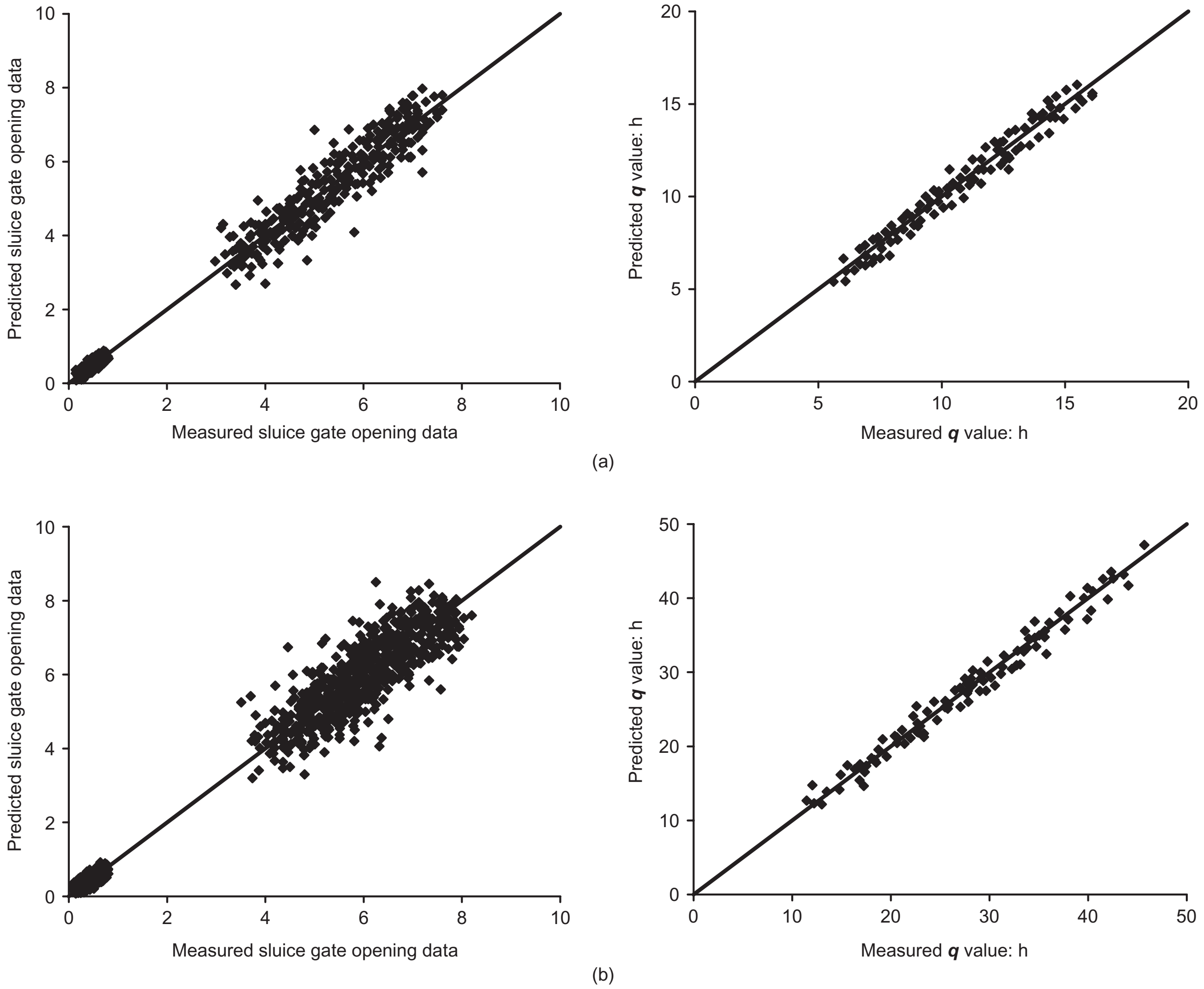

Figure 10. Measured against predicted data at testing stage for (a) water delivery operation model and (b) water drainage operation model

E_1		t_1: h		E_2		t_2: h		E_3		t_3: h	
Measured	Predicted	Measured	Predicted	Measured	Predicted	Measured	Predicted	Measured	Predicted	Measured	Predicted
0·30	0·28	3·57	3·66	0·42	0·36	3·34	3·58	0·60	0·45	3·85	4·08

Table 2. Measured against predicted operation indices of sluice gates for water delivery operation scheme

in the channel network of Pudong New District for better managing the local water resources. In the water transferring experiment, Xigou and Donggou sluice gates were first opened for water drainage at 3:10 am on 19 September, then the remaining five sluice gates for water drainage were opened in turn. At 8:35, 8:45 and 9:00 on 19 September, Sanjiagang, East Zhangjiabang and Wuhaogou sluice gates were opened for water delivery respectively. According to the tide table in the year 2004, the average water levels of the outer rivers during water transfer were obtained. More details of the water transferring experiment are available in Tang *et al.* (2004). The initial computation time of the model was 3:10 on 19 September. As input variables of the operation model, the initial water levels for both the inner and outer rivers, the average water levels of the outer rivers, the expected inner river water level, the sluice widths and the bottom sill elevations were specified. The sluice gate operation scheme was determined by the ANN model. The hydrodynamic model was used to simulate the flow for the water transferring experiment, and the simulation results were compared with the measured data. A comparison between the calculated and measured water volumes for the water delivery and drainage is given in Table 3, which shows that the predicted water volumes for both water delivery and drainage are in good agreement with the measured ones. The relative errors are generally less than 10%. Figure 14 shows the verification of the representative water levels of the inner rivers during the water transferring experiment. It is evident that the computed stage hydrographs are in good agreement with the measured hydrographs and the absolute error is generally less than 10 cm. As a whole, the calculated results are close to the measurements during the water transferring experiment. Thus the artificial intelligence modelling system can be considered as a tool for efficient water resources management.

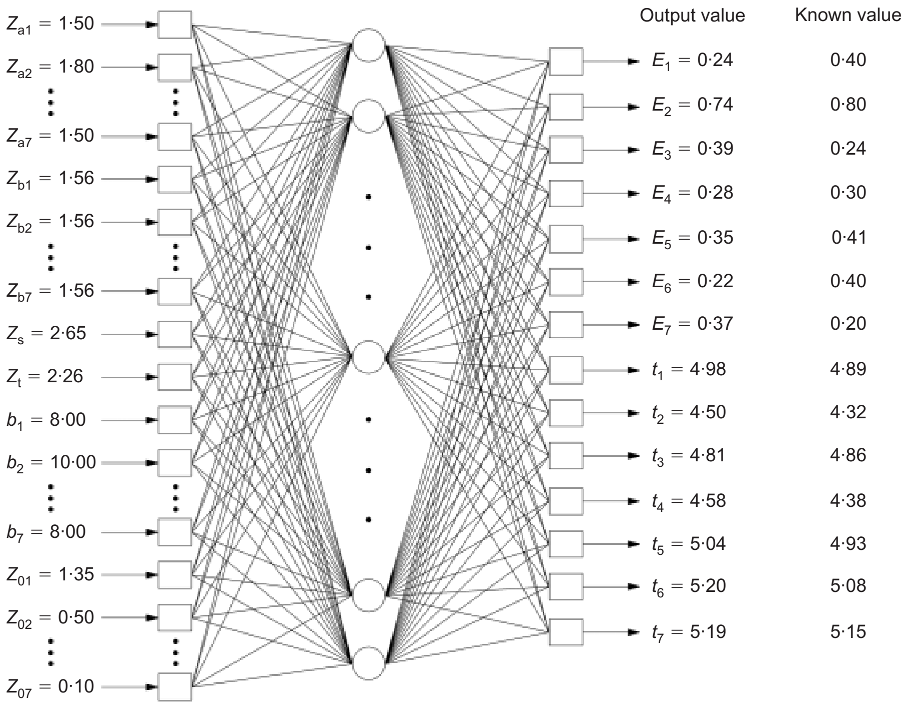

Figure 11. Measured against predicted operation indices of sluice gates for water drainage operation scheme

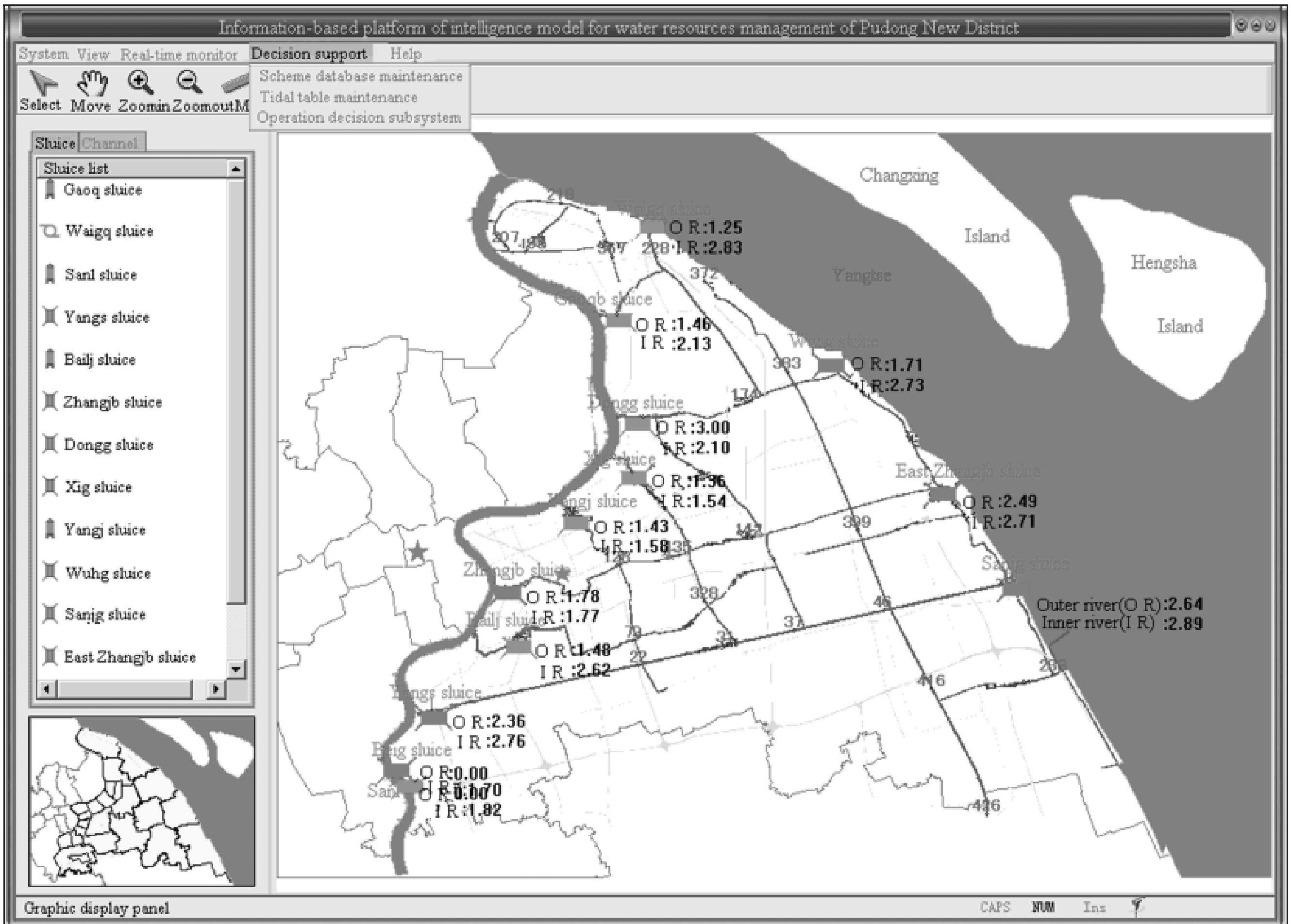

Figure 12. Information-based system for water resources management in Pudong New District

Figure 13. Operation decision subsystem

Sluice	Quantity of water delivery and drainage		
	Measured value: $10^4 m^3$	Calculated value: $10^4 m^3$	Relative error: %
Sanjiagang	798·2	806·1	0·99
East Zhangjiabang	737·9	761·5	3·20
Wuhaogou	229·0	251·6	9·87
Gaoqiao	154·5	150·5	−2·59
Yangsi	361·2	354·8	−1·77
Bailianjing	414·9	444·0	7·01
West Zhangjiabang	336·9	317·7	−5·70
Yangjing	334·3	315·5	−5·62
Xigou	338·4	345·3	2·04
Donggou	434·6	386·2	−11·14

Table 3. Comparison between predicted and measured water volumes for both water delivery and drainage

4.2. Case 2: intelligence operation during a flood

Pudong New District is located at the east of Shanghai City, the lower Huangpu river and the south of the estuary of the Yangtze river. It is a delta region with low-lying topography located at the east of the Yangtze river delta. Under the influence of special geographical conditions and climatic factors, flood prevention is very complicated and floods often occur. Thus it is very important to follow reasonable sluice gate operation procedures for flood prevention. Below is an example of applying the artificial intelligence modelling system to the channel network of Pudong New District to show its usefulness for a flood risk control operation. The flood occurred on 3 July 2002. The initial inner river water level was 2·95 m, and the expected inner river water level was 2·66 m, the initial and average water levels of the outer rivers at sluice gates for water drainage are shown in Table 4. According to

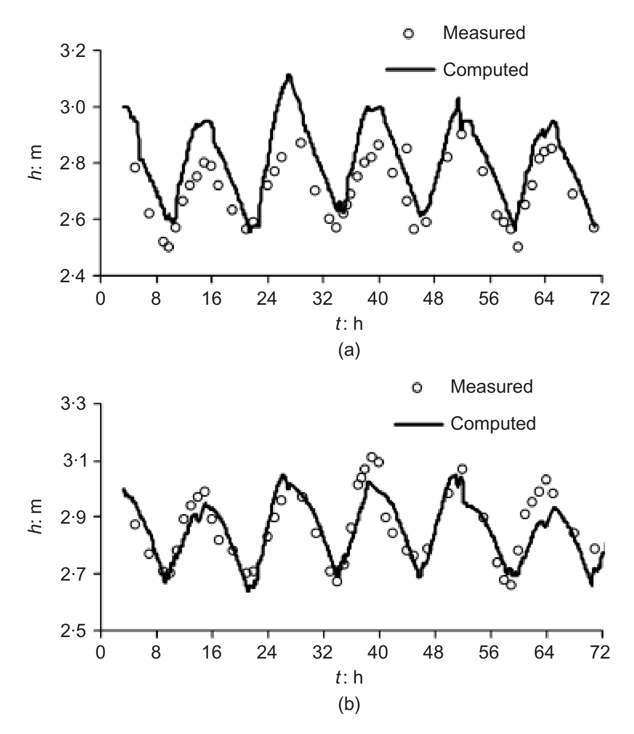

Figure 14. Comparison between measured and calculated stage hydrographs at: (a) Jinjiazhai station; (b) Zhaoqiao station

Sluice	Water level: m	
	Initial value	Average value
Yangsi	2·50	2·20
Bailianjing	2·50	2·19
West Zhangjiabang	2·51	2·21
Yangjing	2·50	2·20
Xigou	2·49	2·19
Donggou	2·47	2·18
Gaoqiao	2·46	2·18

Table 4. Initial and average water levels of the outer rivers at sluice gates for water drainage

these known parameters, the sluice gate operation schemes shown in Table 5 were obtained from the trained ANN model for the water drainage operation. Then the hydrodynamic model was used to produce the discharge hydrographs at the sluice gates and the corresponding water levels. Figure 15 presents the discharge hydrographs at the seven sluice gates during the water drainage event. The stage hydrographs at the six gauging stations are shown in Figure 16. It can be seen that the average stable water level of the inner rivers is reduced to 2·68 m after the sluice gate operation, which generally meets the expected demand. It is indicated that the inner river water level can be controlled within a reasonable range to minimise the loss caused by emergent disasters.

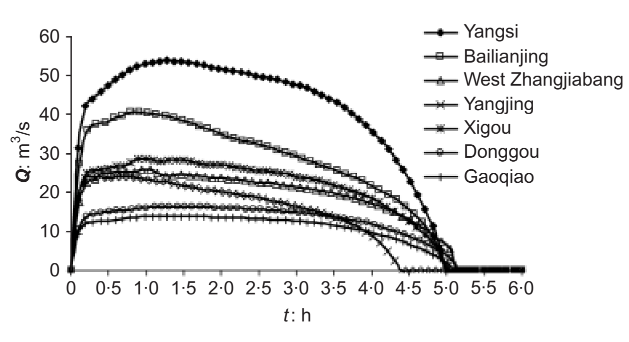

Figure 15. Discharge hydrographs at seven sluice gates during water drainage

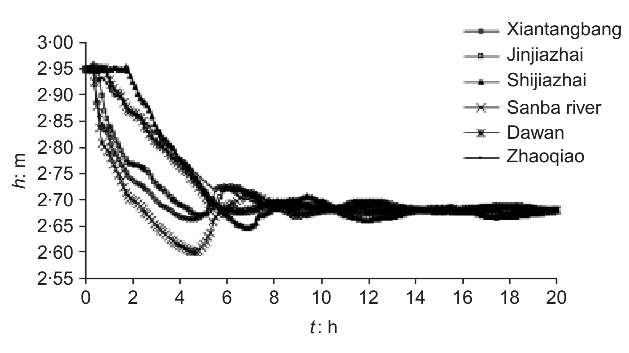

Figure 16. Stage hydrographs at six gauging stations during water drainage

5. CONCLUSION

To overcome the existing problems in water resource management for the channel network in Pudong New District, an artificial intelligence modelling system was developed for managing the water resources. The system is composed of an ANN model for controlling sluice gates and a hydrodynamic model for simulating flow in channel networks. Using the data obtained from the water transferring experiment in September 2003, the ANN model of sluice gate operation was trained and tested, and the calibration of the hydrodynamic model was also performed. The artificial intelligence modelling system for water resources management was then applied to the water transferring experiments in the channel network of Pudong New District carried out in September 2004. A good agreement was attained between the predicted and measured water delivery and drainage volumes and water levels. The artificial intelligence modelling system was also applied to a flood risk control operation in the channel network of Pudong New District. The results indicate that the average water level of the inner rivers can be reduced to a reasonable range. It can be concluded that the artificial intelligence modelling system developed in this study can meet the demands for intelligent management of water resources for large-scale complex channel networks, such as the channel network of Pudong New

E_1	t_1: h	E_2	t_2: h	E_3	t_3: h	E_4	t_4: h	E_5	t_5: h	E_6	t_6: h	E_7	t_7: h
0·47	5·01	0·37	5·02	0·21	5·14	0·46	4·41	0·24	5·00	0·31	5·15	0·47	5·11

Table 5. Output water drainage operation scheme

District. This in turn can bring in useful economic and social benefits in managing sluice gate operation, water level controlling of the inner rivers, water volume calculation and some other aspects.

ACKNOWLEDGEMENTS

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