Real-Time Reservoir Operation for Flood Control Using Artificial Intelligent Techniques

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Abstract

Real-time reservoir operation for flood control is a continuous and instant decision-making process based on relevant operating rules, in addition to the immediate rainfall and hydrological information. To reduce downstream flood peak stage and store floodwaters for future use, reservoir operation for flood control plays a critical role. The aim of this study is to establish a real-time reservoir operational model, the intelligent fuzzy flood control model (IFFCM), for flood control to ensure reservoir safety and store floodwaters for future use. The model includes two major artificial intelligent processes: knowledge acquirement and implementation, and fuzzy inference system. The IFFCM is first built by extracting the knowledge from the optimal operating hydrographs of typhoon events obtained by genetic algorithm (GA) and is then inferred reservoir release by the adaptive network-based fuzzy inference system (ANFIS). The Shihmen Reservoir in northern Taiwan is used as a case study with particular attention to the operations of 26 flood events by the proposed method. The results demonstrate that the proposed model can perform much better than historical reservoir operations and effectively reduce downstream peak flood stage and store floodwaters for future use.

Keywords: Reservoir flood control, Adaptive network-based fuzzy inference system (ANFIS), Genetic algorithm (GA), Real-time decision-making process.

1. Introduction

Reservoirs are man-made lakes constructed for civic purposes, such as water supply, irrigation, hydroelectric power, flood control, and recreational development. Today, more than 41,000 large dams and reservoirs exist worldwide and water becomes increasingly valuable. As a result of these activities, 60% of the 227 largest rivers in the world are longitudinally fragmented by dams or other human-made infrastructure (Revenga et al., 2000). Many reservoirs operate for flood

protection as well as other types of water resource management purposes. To make sustainable utilization of water resources, while avoiding possible damage to dams and downstream areas, the optimal flood control of reservoir operation is undoubtedly important. Nevertheless, reservoir operation of dams during floods is a continuous and instant decision-making process based on relevant operating rules and water laws that is significantly affected by hydrological conditions which present high degree of uncertainty. Taiwan, located in the subtropical monsoon zone of the North Pacific Ocean, has an annual average rainfall of around 2,500mm and of high seasonal variability. Typhoon related rainfalls have been recorded over 1,000 mm/day. Because the mountainous terrain and

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steep landform rapidly accelerates the speed of the accumulated rainfall flows and makes most of the rainfall flow straight into the ocean within a few hours, rivers cannot be a stable source of water supply due to their inability to keep enough water for use. Reservoirs have thus become the most important and effective floodwater storage facilities. However heavy rainfall often surpasses reservoir capacity, which makes reservoir operations more than critical in mitigating tremendous inflows to ensure dam safety and reserve floodwaters for stable water supply.

As mentioned above, there is a strong need to explore tools that can realistically represent the complex systems, continuously solve the multi-criteria decision-making problem and make reliable reservoir operation models for disaster prevention. In the last decade, the development of optimal reservoir operation methodologies for flood control has been very active. Hasebe and Nagayama (2002) applied fuzzy and neural network system analysis to a dam operation support system. Westphal et al. (2003) built decision support systems for obtaining reasonable flood control operating schedules. Cheng and Chau (2004) presented a software integration flood control management system for reservoirs. Yang et al. (2004) developed a coupled distributed hydrological model to flood control. Karbowski et al. (2005) calculated water releases on the basis of inflow forecasts and expert knowledge and applied them to real-time reservoir operation. Ngo et al. (2007) proposed a combination of simulation and optimization models for the Hoa Binh reservoir flood control operation. Even though a great number of promising results and considerable progress have been made, researches related to real-time reservoir operation have still migrated rather slowly in finding its way into practice. Cheng and Chau (2004) stated that most of the existing flood control systems for reservoirs were established for special purposes and lacked data sharing and communication; consequently, it is very difficult for decision-making authorities to get real-time information within a short time. Hansson et al. (2008) also mentioned that many governments lack an adequate in-

stitutional system for applying cost-effective and reliable technologies for disaster prevention and early warnings.

Artificial Intelligence (AI) deals with helping machines to find solutions to complex problems in a more human-like fashion. It is known that incorporating artificial intelligence into control systems allows these systems to be more flexible, and to include human expertise and thinking into their decision-making process. Artificial intelligence tools such as the artificial neural network (ANN), genetic algorithms, and fuzzy logic approaches have been proven to be efficient in a variety of problems when applied individually or in combination with each other (the latter results in the so-called neuro-fuzzy systems). ANNs are known as flexible modeling tools with capabilities of learning the mathematical mapping between input and output variables of nonlinear systems and have been quite successfully used for different hydrosystem problems (e.g., Jain et al., 1999; Chang and Chang, 2001; Ponnambalam et al., 2003; Wei and Hsu, 2008). Fuzzy logic has good ability for describing human thinking and reasoning in a mathematical framework. The development and adoption of fuzzy logic for planning and management of complex water resources systems has become popular (e.g., Hundecha et al., 2001; Chang et al., 2002; Dubrovin et al., 2002; Fu, 2008). ANFIS can help extract the fuzzy if-then rules from input-output data pairs when expert knowledge is not directly available. Successful applications of ANFIS in different fields have already been reported (Gao and Ovaska, 2001; Zhang and Roy, 2001; Chang et al., 2005; Chang and Chang, 2006).

Given the large number of high-risk situations as well as the extremely high costs in terms of casualties and damages involved in flooding, the implementation of flood control aimed at its reduction becomes essential from a holistic view of the problem. The main purpose of this study is to establish an intelligent real-time reservoir operation model for flood control to ensure reservoir safety and store floodwaters for future use. The intelligent model includes two major AI processes: the knowledge acquirement and implementation,

and the neuro-fuzzy inference system. The Shihmen reservoir in northern Taiwan is used as a case study with particular attention to the operations of 26 flood events by the proposed method.

2. Methodology

Intelligent control is a state-of-the-art technology and has been well recognized for its remarkable ability in controlling complex systems. In this study, an intelligent real-time reservoir operation module for flood control is proposed. The intelligent module assembles three major procedures: the genetic algorithm (GA), the adaptive network-based fuzzy inference system (ANFIS), and the automatic spillway operation. The GA is used to search the optimal reservoir flood operating hydrographs based on historical inflow series of 26 flood events. Based on these optimal inflow and release hydrographs (input-output patterns), the ANFIS is then trained to configure the fuzzy inference system, build the suitable structure and parameters of the network, and continuously infer the optimal water release according to current reservoir watermark and inflow situation. An automatic operation of the spillway can continuously proceed according to the optimal release inferred by ANFIS. In the following sections, the methodology of intelligent flood control system and corresponding theorems, i.e., GA, ANFIS, and automatic control of spillway, are first briefly introduced. The framework is shown in Figure 1.

Genetic algorithm

The genetic algorithm (GA) is based on Darwinian natural selection with the mechanisms of population genetics. It has been widely applied to solving a great number of water resources problems (Cai et al., 2001; Chang and Chang, 2001; Chang, 2008). The GA tends to mimic natural evolution: the variables are first coded as a string, and then a set of candidate solutions is created. The evolution starts from coded solutions and proceeds from generation to generation

through genetic operators: reproduction, crossover and mutation. As the aforementioned genetic operators proceed, the optimal goal will eventually be achieved. GAs are usually designed for finding the optimum solution to complex unconstrained optimization problems; consequently, they have to adapt themselves to handle constraints. Many researchers have proposed effective penalty functions to improve the efficiency of GAs (Deep and Dipti, 2008; Katsifarakis and Petala, 2006; Chang et al., 2010). The penalty-type GA is applied to searching the optimal reservoir release hydrographs based on historical inflow series of 26 flood events.

Adaptive network-based fuzzy inference system

The procedure of developing a fuzzy inference system (FIS) based on the architecture of ANN is called an adaptive network-based fuzzy inference system (ANFIS), introduced by Jang (1993). FIS and ANN share the respective ability to improve the intelligence of systems working in uncertain, imprecise, and noisy environments. ANFIS combines the advantages of artificial neural networks (e.g., learning ability, optimization, and connectionist structures) and FIS (e.g., extracting fuzzy rules from numerical data). It eliminates the basic problem in fuzzy systems designed by effectively using the learning capability of ANN for automatic fuzzy rule generation and parameter optimization. ANFIS is widely used in hydrology and water resources issues (Chang and Chang, 2001; Lin et al., 2005; Kisi, 2008; Wang and Elhag, 2008). This network is a five-layer feedforward network that uses neural network algorithms coupled with fuzzy reasoning to map an input space to an output space. Details of the ANFIS algorithm can be found in Chang and Chang (2001).

Automatic control of spillway gates

A spillway is a structure used to control the water release from a dam into a downstream area. A controlled spillway has mechanical gates to regulate the flow rate so that water

Fig. 1: Framework of real-time intelligent flood control systems

does not overtop and damage the dam. The released outflow rates of reservoir water must be arranged carefully by suitably controlling the spillway gates of a dam. The minimum and maximum water levels of the Shihmem Reservoir are given as 237.5 m and 252.5 m, respectively. The water flow is adjusted by opening or closing the spillway gate with settings

from 0 up to 12 m, which is the fully open case. Relations of spillway gate opening and the actual release quantity can be found in Figure 2. There are six tainter floodgates of concrete ogee-type spillway, each of 14 m x 10.61 m with minimum discharge rate of $600 \text{ m}^3/\text{s}$ and maximum discharge rate of up to $11,400 \text{ m}^3/\text{s}$.

Fig. 2: Relations of spillway gate opening coupled with water level and inflow hydrograph vs. water release

3. Application

The Shihmen Reservoir, located upstream of the Tahan River (Figure 3), satisfies multiple purposes of irrigation, hydropower generation, industrial and domestic water uses, flood control, and recreation. The Tahan River has a length of 135 km with an average channel slope of 1/37, and its watershed covers an area of 1163 km². The watershed receives an average annual rainfall of 2,410 mm in the last 40 years; however, rainfall is uneven — over 70% occurs between May and October (typhoon season). The watershed of the Shihmen Reservoir covers an area of 763.4 km² with an effective storage capacity of 2.35×10^8 m³. The crest elevation of the dam is 252.1 m, the top of the flood control pool is at

an elevation of 250 m, the normal maximum water level of the conservation pool is 245 m, and the dead water level is 195 m.

The available data

The historical hourly inflows and operation hydrographs of the Shihmen Reservoir were collected and used to evaluate the reliability and effectiveness of the proposed modules. Twenty-six typhoon events were collected from the past 35 years (1971-2005), published by the Water Resources Agency (WRA), Taiwan. These typhoons had different peaks, durations, initial water levels, and are divided into four different categories according to the amount of floodwater shown in Table 1; “small” (denoted 1) means the total volume of floodwater is less than 70% of the capacity of Shihmen Reservoir; “medium” (denoted 2) is between 70% and 100%; “large” (denoted 3) is

between 100% and 200%; the remaining events with floodwater volume more than twice the capacity of Shihmen Reservoir belong to “huge” (denoted 4); therefore, the corresponding operation is particularly important.

3.1 The Formulation of Reservoir Operation for Flood Control

GA for searching release hydrographs

As mentioned above, the Shihmen Reservoir is a multi-purpose reservoir, so its optimal operation should always ensure dam safety while the final water level reaches the

target level and water releases minimize the release peak for alleviating downstream damage. The goal is to optimize the objectives while complying with relevant regulations and physical constraints. The GA is used to identify a series of releases and water levels of the reservoir based on given inflow series of a flood event. Due to a great number of constraints and flood control requirements, it is difficult to reach a feasible solution without violating constraints. To tackle this bottleneck, a proper penalty strategy for each parameter is used to guide the GA searching process. Details of formulation can be found in the previous study (Chang, 2008).

Fig. 3: The locations of the Shihmen Reservoir and the Tahan River

Table 1
Collected hourly data of typhoons (1971-2005)

Event	Date	Duration (hr)	Total volume of floodwaters (10^8 m^3)	Peak (cms)	Water level(m)		Category
					initial	Target	
Bess	1971/9/22~9/24	53	3.13	5172	238.9	240	3
Irving	1979/8/14~8/16	42	1.63	2006	225.23	240	1
Maury	1981/7/19~7/21	38	1.33	2217	232.38	236	1
Nelson	1985/8/22~8/24	44	2.79	4906	233.91	240	3
Abby	1986/9/18~9/20	36	1.43	2129	239.09	240	1
Gerald	1987/9/9~9/10	25	0.74	1444	241.62	240	1
Sarah	1989/9/11~9/13	68	3.32	2959	237.82	240	3
Yancy	1990/8/18~8/20	43	2.24	4344	231.88	240	2
Abe	1990/8/30~8/31	42	2.32	3604	243.33	240	2
Dot	1990/9/7~9/9	52	2.18	2593	242.08	240	2
Omar	1992/9/4~9/5	22	0.48	870	242.08	240	1
Doug	1994/8/7~8/9	37	1.98	3065	235.82	240	2
Fred	1994/8/20~8/22	37	1.56	2440	238.82	240	1
Herb	1996/7/31~8/2	55	3.99	6363	231.38	240	3
Winnie	1997/8/17~8/19	50	2.65	3411	236.72	240	3
Zeb	1998/10/15~10/17	54	2.97	4643	239.92	245	3
Bilis	2000/8/22~8/24	36	1.20	2230	237.37	240	1
Xangsane	2000/10/31~11/2	30	1.06	1852	237.43	245	1
Nari	2001/9/16~9/19	83	4.88	4124	236.45	240	4
Lekima	2001/9/25~9/28	72	2.21	1505	238.04	240	2
Aere	2004/8/23~8/27	73	7.03	8594	242.20	240	4
Haima	2004/9/11~9/13	40	1.27	1637	241.70	240	1
Nockten	2004/10/25~10/26	32	0.74	958	242.51	245	1
Haitang	2005/7/17~7/19	46	2.01	3199	237.55	236	2
Masa	2005/8/4~8/6	63	4.87	5322	239.39	240	4
Talim	2005/8/31~9/2	38	1.78	3689	240.66	240	2

Category: 1-small; 2-medium; 3-large; 4-huge

Fig. 4.: The constructed ANFIS for on-line reservoir operation for flood control

ANFIS formulation

To configure and test the ANFIS model, 26 operating hydrographs of typhoon events obtained from GA method are used and divided into two independent sets: training and testing. The selection of the ANFIS model is based on the assumption that the ANFIS model with the smallest RMSE (root mean square error) in the training process has a greater potential of achieving a lower RMSE in follow-up processes. The RMSE statistic measures the residual variance of the model and is used to quantify the error between GA's operating hydrographs and the model's estimated values. To construct an on-line operating model, (1) the inflow, (2) the peak information (before peak: 1, after peak: -1), (3) the target water level after flood operation (shown in Table 1), and (4) the current water level are selected as input variables. The peak information is designed to judge whether the current inflow condition is before or after the peak; and the target water level solely depends upon the time (month) of a given flood event.

Since each input variable might have several values (in terms of rules) and each rule includes several parameters of the membership function in layer 2, these will be a huge number of parameters to be determined as the number of rules is increased. To solve this problem, the subtractive fuzzy clustering is used to establish the rules (Chang and Chang, 2001). A number of clusters have been evaluated, and it is found that three cluster rules can produce a relatively small RMSE while concise structure (Figure 4). Three identified membership functions of four input variables are shown in Figure 5. Since there are only three clusters, the inference system becomes quite simple.

The total number of parameters is only 39 including 15 linear parameters ((4 variables + 1) * 3) and 24 nonlinear parameters (4 variables * 2 Gaussian's coefficients (center and standard deviation) * 3 rules). After the training process completes, the constructed ANFIS model can then be used to estimate the on-line water release based on a set of four input variables' values. As the on-line estimation of water release proceeds continuously, the model can systematically

come out with the hydrograph of water release for a given flood event.

4. Results

Assessment of flood control virtually comprise of storing water in reservoirs and regulating the flow so that the river downstream can safely accommodate and carry over it. Through formulating the reservoir operation for flood control as an optimization problem, the penalty-type genetic algorithm was used to find the release hydrograph in the reservoir operation for flood control for each given flood event to fulfill the minimization of release peak as well as comply with the regulations and restrictions. The results of 26 flood events obtained by the penalty-type GA method and the historical reservoir operation are briefly summarized as follows. The historical operations could suitably control and postpone the flood peak during typhoon events, but the final storage of six events did not reach the target and the decreasing rates of flood peaks of nine events were less than 0.1. On the other hand, the penalty-type GA would effectively decrease the flood peak, meet the target storage and postpone the flood peak (from 2 to 7 hours). Table 2 summarizes the average results of four categories of typhoons (small, medium, large and huge) by three methods. For large typhoon events, the GA can have much greater decreasing rates of flood peaks than historical operation: 30% for GA and 13% for historical operation. The GA can postpone the arrival time of a peak up for five hours, while the historical operation can only postpone the arrival time of a peak for two hours for larger typhoon events. Most large typhoon events produce smaller outflow peaks by penalty-type GA than by historical operations. The lower releases during the final stage of a flood will keep the water level lower within safety range during the operation of flood control. In general, the GA have much better performances than the historical operation. However, even though the GA can have much better performance than the historical operation, it cannot be used for on-line operation purpose because the water

release hydrograph is the searched result based on a given inflow hydrograph, which means the foreknowledge of inflow hydrograph is available and that is not the normal case.

To overcome this problem, the ANFIS model is proposed to implement to learn the major characteristics of the input-output patterns (inflow and outflow hydrographs) obtained from the GA searched hydrographs. For training and testing the ANFIS, 26 typhoon events are divided into training and testing sets by assigning 824 data sets from 18 events as training data and 387 data sets from the remaining 8 events as testing data. 39 parameters of the constructed model can be optimized through training process by using the training data, and the model performance can be validated by the independent test data. The RMSE between GA and ANFIS results for training and testing processes are 274 and 350, respectively. It claims that the ANFIS models are suitable and consistent. Besides, the correlation coefficients between the GA searched hydrographs and ANFIS referred water release hydrographs are 0.98 and 0.94 in training and testing events, respectively, which are very close to unity. It appears the ANFIS model can make excellent and consistent performance and its on-line water release hydrographs in all 26 events are similar to the optimal water release hydrographs obtained by GA. These results provide conformably evidences that the ANFIS model has a great ability to learn from input-output patterns which can be assumed to represent the reservoir's hydrology and human knowledge.

For the purpose of profound assessment and comparison between the historical operation and ANFIS, the collected typhoon events are divided into four categories based on the amount of their floodwater and the models' performances are summarized as follows.

The small typhoon events: 1st category

Ten typhoon events belong to the 1st category. For this type of event it is easy to make the operation strategy of flood prevention because of small flow quantity. The

major concern of the operation schema for this kind of event is the final storage, where the reservoir water level should reach a certain target level. Table 3 shows all maximum water levels in this category are below 248 m (the upper limit) and the average flood peak reduction rate is 26% (Table 2). The model performance is good and reliable in this type of typhoons.

The medium typhoon events: 2nd category

Seven typhoon events belong to the 2nd category. The average flood peak quantity of

these events surpassed 3000cms. They would not pose intense threat to downstream area; however, reducing the peak discharge might reduce the risk of flooding of downstream low-lying areas. Table 2 shows that the flood peaks can all be effectively reduced and the average flood peak reduction rates are 24% and 17% by the proposed model and historical operations, respectively. Table 3 indicates the final water levels in all 7 events are very close to the target water level by the ANFIS model for the 2nd type events.

Table 2
Comparison of three models based on the average of four categories of typhoons

Events	Operator			GA			IFFCM		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Small	0.26	655	6	0.35	381	5	0.25	455	3
Medium	0.17	726	5	0.28	276	4	0.24	599	2
Large	0.13	660	2	0.30	168	5	0.27	588	4
Huge	0.07	724	0	0.23	543	2	0.11	384	1

- (1) the decreasing rate of flood peak
- (2) the release flow in the end of operation (cms)
- (3) the postponed arrival time of flood peak (hours)

(a)

Fig. 5:. Membership functions for (a) inflow (b) peak information (c) target water level (d) current water level

Table 3

Comparison of the flood operating results
between historical and IFFCM

Category	Typhoon	historical				IFFCM			
		(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
1	Irving	0.54	242.7	241.3	835	0.33	239.4	238.5	506
	Maury*	0.61	242.5	240.7	726	0.48	240.2	237.6	671
	Abby	0.34	246.0	242.5	970	0.15	241.7	239.6	541
	Gerald	0.35	245.0	242.2	861	0.21	242.5	241.0	713
	Omar*	-0.41	242.1	238.8	782	0.08	242.4	241.7	656
	Fred	0.34	242.4	238.9	936	0.21	241.6	239.3	485
	Bilis	0.62	243.6	243.6	132	0.32	240.0	238.8	446
	Xangsane*	0.11	243.9	242.7	494	0.44	243.3	243.3	0
	Haima	0.04	243.5	241.8	352	0.10	243.0	240.3	533
	Nockten	0.07	242.5	241.9	467	0.17	244.7	244.7	0
2	Yancy	0.53	245.9	242.1	984	0.39	243.2	240.1	669
	Abe	0.15	247.8	240.7	1039	0.17	245.0	240.4	705
	Dot	0.16	244.9	239.1	796	0.16	243.6	239.3	592
	Doug*	0.13	245.4	241.4	918	0.25	242.9	240.3	646
	Lekima*	-0.11	241.4	238.9	314	0.20	240.4	238.3	496
	Haitang	0.16	241.4	239.3	502	0.25	241.4	237.5	454
	Talim	0.16	243.1	242.2	527	0.27	243.5	240.0	632
3	Bess	0.25	245.2	243.5	796	0.26	245.3	239.4	612
	Nelson	0.09	245.4	238.5	720	0.29	244.8	240.7	708
	Sarah	0.27	246.5	240.9	879	0.24	243.1	239.3	598
	Winnie*	0.08	244.1	244.0	305	0.23	243.4	239.7	558
	Zeb	0.01	244.6	243.4	530	0.34	248.0	244.8	470
	Herb*	0.15	245.3	242.2	732	0.24	246.3	240.6	583
4	Nari*	0.16	245.2	242.8	809	0.19	245.0	239.1	522
	Aere	0.01	245.8	242.8	652	0.04	247.9	240.1	0
	Masa	0.03	245.3	239.9	710	0.10	246.9	240.3	631

- (1) The decreasing rate of flood peak (%)
- (2) The highest water level during the period of operation (m)
- (3) The final water level (m)
- (4) the release flow in the end of operation (cms)

*: testing events

The large typhoon events: 3rd category

Six typhoon events belong to the 3rd category. Their total inflow quantities were situated between 100%~200% of the reservoir available capacity. The operators must give dual attention to both dam security and the reduction of flood peaks to prevent life and property from loss in downstream area. Tables 2 and 3 show the results of the 3rd type events. The average reduction rate of flood peaks is increased from 13% to 27% as the proposed model is implemented, and the final water levels of the proposed model are also much closer to the target levels than those of the historical operations in all the events except Typhoon Zeb.

The huge typhoon events: 4th category

Only three typhoon events belong to the 4th category. Their total inflow quantities were over 200% of the reservoir available capacity. In fact, the total inflow quantity of Typhoon Aere was more than three times the capacity of the reservoir. The average flood peak quantity of these events was more than 6000 cms. In this circumstance, the operation strategy of flood prevention should take dam security as the most important consideration; while the flood peak reduction rate and the final water level can only be considered as minor or secondary objectives. Tables 2 and 3 present the results of the 4th type events. They show that the historical operation could only provide limited effects on peak flood reduction, while the ANFIS model could give an average reduction rate of 11% on flood peaks. Regarding the final water level, the ANFIS, again, can always be close to the target level as it should be.

A graphical representation of the comparison between the actual hydrographs and the ANFIS operating hydrographs of Typhoons Nari (huge) and Winnie (large) is presented in Figure 6. It appears that the ANFIS model can offer suitable and preferable hydrographs of the water levels during typhoon events. It shows that the ANFIS model has (1) small discharge during the peak period, (2) lower water level most of the time during the

(a) Typhoon Nari

(b) Typhoon Winnie

Fig. 6.: The hydrographs of discharge, water level, and the number of spillway gate opening for Typhoons (a) Nari and (b) Winnie

flood event, and (3) more opening of gates all the time except when near the peak flow than the historical operation. The idealistic results indicate that the ANFIS model well fits the nonlinear relationship between the inflows and the state variables (optimal water levels). The results well demonstrate that the ANFIS can be successfully applied to establishing an intelligent reservoir operation system for flood control that can provide accurate and reliable water level estimation.

Conclusion

In this study, an artificial intelligent methodology was proposed to build a real-time reservoir operation system for flood control.

The Shihmen Reservoir, the most important water facility in north Taiwan, is used as the case study. The historical reservoir's inflow and operating hydrographs of 26 typhoon events of the last thirty-five years were collected and used for model training and testing. The results suggest that the GA provides an adequate, effective and robust way to search the optimal reservoir flood operating hydrographs. Based on the historical inflow (input) and GA's searched operating hydrographs (output), ANFIS is implemented to learn from the input-output patterns, to create the fuzzy inference system, and then to perform the on-line reservoir operation for flood control. The approach demonstrates that the proposed intelligent real-time reservoir flood control model can effectively decrease the flood peak, save floodwaters and keep the dam safe.

The results obtained in this study can be of valuable use for flood mitigation of the reservoir operation. Undoubtedly, operating an important reservoir during crucial conditions such as flooding should strictly follow the reservoir operating rules (or laws), while in many unforeseen situations the experienced human operators are the key to making a successful and reliable decision. However, owing to human factors and highly uncertain hydro-geo-meteorological conditions, there is no guarantee of the safety and efficiency of the operating process. The AI methodology

proposed in this study could efficiently deal with vast and complex input-output patterns, and present an efficient way to train and build up a neuro-fuzzy inference system for reservoir operation for flood control. The results of the study are highly encouraging and suggest that the AI approach is viable for better understanding and modeling reservoir operation for flood control.

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