

## ***Interactive comment on “Auto-control of pumping operations in sewerage systems by rule-based fuzzy neural networks” by Y.-M. Chiang et al.***

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Please note that the full text of AC reply is uploaded to Supplement file. Thank you!

We sincerely thank the reviewer for being interested in our article and for providing important and valuable comments and suggestions. The responses to the reviewer's concerns are described as follows. The relevant responses and corrections in consideration of the reviewer's suggestions are revised in the manuscript (underlined) as well.

RC 1: I think the paper is well written and organised. However, I believe there are two major issues the authors need to address. First of all, it is not clear what is the gain

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in performances provided by the proposed techniques with respect to traditional methods for managing the pumping station. Second, I believe the presentation is not clear in some of the sections. Concerning my first remark above, I think the paper suffers from a lack of comparison between the proposed neural network techniques and traditional management of the pumping station. The authors only present the comparison between two different types of neural networks, but the reader is left wondering if neural networks provide a real advantage with respect to traditional techniques. In other words, the paper misses the comparison with a baseline operating rule. How is the pumping station managed today? What would be an alternative technique to manage it if neural networks were not used? Are neural networks really providing a consistent advantage? In fact, it seems that neural networks are used to predict the number of operating pumps only, depending on aggregate inputs like the number of open gates. Usually, these systems are managed in practice by automatically activating the pumps when the water level reaches given thresholds. Is such kind of procedure currently used in Taipei City? I believe the reader needs more details and needs to know if neural networks are indeed providing an added value in this case.

Response 1: We agree with the reviewer's view that “the sewerage system should be managed in practice by automatically activating the pumps when the water level reaches given thresholds”. In fact, the original operating procedure of the Yu-Cheng pumping station followed such a concept when it was built in 1980s. Figure below shows the original design of the operating procedure. However, due to global climate change and urbanization, extreme rainfall events usually bring torrential rainwater and result in fast floods in Taiwan. Therefore, the original design of the operating procedure is not able to accommodate the rainfall-runoff phenomenon nowadays. As current operating mechanism used in Yu-Cheng station, there are no explicit guidelines for pumping operations but are highly dependent on the experiences of operators with the only goal of controlling the water level under 2.4 m (Lines 244-250) Generally, the 7 pumps arranged in Yu-Cheng station are operated in a sequential order according to the changes of water levels. When a running pump cannot control the water level

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under the level of 2.4 m, another pump will start working. On the contrary, the pumps are turned off sequentially as the water level is decreasing. Operators have to stand by prior to the coming of extreme rainfall events and keep monitoring and operating until storms' departure. It is time and human resources-consuming. In sum, the pumping station is operated by experienced operators to adjust the status (on or off) of the pumps according to the actual precipitation and the changes of water levels (Lines 250-253). Besides, both original and current operations do not contain any message for future water levels, and thus are less efficient than the proposed forecasted operating model in terms of time.

The original design of the operating procedure for Yu-Cheng pumping station (refer to Fig. 1 attached).

Regarding the comparison, to our best knowledge, there is no other traditional approach being used to simulate the system. One way to show how a system responds to an input is to collect the historical records and then analyze the input-output relation. If a robust relation between input and output can be found, it can be used for future operation when similar input situation occurs. Therefore, we proposed the rule-based fuzzy neural networks that learned from circumstances, predictive information, and historical pumping operations made by the experienced operators (Lines 305-311), and thus not only gave an accurate and reliable auto-control of pumping operations but also provided forecast information on operating the pumps. This is the very first study using the AI techniques to simulate the drainage mechanism for discharging rainwater and reducing the risk of flood in advance (Lines 311-313). This proposed mechanism was originally funded by the Water Resources Agency of Taiwan and is used as a reliable reference tool that provides valuable operating decisions to assist the operators in advance (20 minutes prior to real status). Besides, results obtained from the operating model in the testing phase (consisted of six typhoon events that occurred during the periods of 2006 to 2008) showed that the outputs of the model maintained a consistent performance (Tables 5 and 6 in the manuscript). Therefore, the proposed fuzzy control

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system is considered to have a great capability to learn from human knowledge (experience) and make suitable decisions (as the experienced operators) and is able to provide consistent and reliable performance (Lines 458-463).

RC 2: Concerning my second remark above, I believe Section 2.1 is not clear. A sketch of the network would be useful here. What is the meaning of the weights in connection with the "if" and "then" rules? Also, the meaning of in section 2.1.1 is not clear as well. Finally, it is not clear to me if the learning rates and are calibrated.

Response 2: Thank you for the valuable suggestion. The architecture of a CFNN has been added in the manuscript (Figure 1). (Fig. 2 attached) Figure 1 The architecture of CFNN with training procedure. The connections between the input layer and the Kohonen layer are indicated as which is an "if" statement of rule-base control, while the connections between the Kohonen layer and the Grossberg layer are which is the "then" statement of rule-base control. Thus, the statement of each rule is defined as: 'if X is w, then Y is (Lines 138-142). The meaning of  $\Delta$  represents the width of the rule. Data with distance (input data and the nearest center) less than  $\Delta$  are classified into the same rule. In this study, the value of  $\Delta$  is optimized by using trial-and-error method (Lines 145-148) and is implemented into the proposed CFNN for modelling the pumping station operation. Besides, both learning rates and are calibrated during the model training phase (Lines 152-153).

RC 3: In Section 2.1.2, I do not understand whether the appropriateness of the Gaussian membership function is checked in some way, in comparison with alternative solutions.

Response 3: For calculating the degree of membership, the Gaussian function has been frequently suggested in literatures and popularly applied in various fields. Besides, the Gaussian function generally provides a more flexible degree of membership and thus produces more appropriate results than the triangular function based on our previous experiences (Chang and Chang, 2001). Therefore, the Gaussian function was

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selected to represent the degree of membership (Lines 164-168) defined as follows.

Equation is shown on Fig. 3 attached.

where  $w_{ij}$  is the center of rule  $j$ ,  $\Delta$  is the width of rule  $j$ , and  $n$  is the number of inputs. In this study, both center and  $\Delta$  were calibrated during the training phase to find out the optimal values for pumping operations.

RC 4: The output from the neural network is the number of operating pumps. Would it be possible to disaggregate the output in some way? Are the pumps really operating in such way that the total number of working units is the only meaningful variable? The same reasoning applies for the input variable "total number of open gates". For a given number of open gates, is the sewer system not sensitive to the actual status of each gate?

Response 4: The reviewer has raised a very interesting and important point. The number of operating pump is direct and useful information for guiding the operator, while it is also the simplest variable (output) for ANN to learn and to model. The Yu-Cheng station contains 7 massive pumps with the same capacity each (see Fig. 2). The activation of 7 pumps is operated in a pre-designed order, which makes no difference of the discharge capability for individual pumps. Prior information of the total number of running pumps can be a great reference to operators, especially when a fast flood occurs. By investigating the pumping operation of Yu-Cheng station, the total number of running pumps (represents the total capacity of pumping water) for model output is a simple and meaningful variable and directly fits the need of operators (Lines 271-277). The reviewer's concern on disaggregating the output is a practical issue and could be constructed by a multi-output neural network. It would be useful to construct a multi-output structure to reflect the relation between inputs and individual pumps if the pumps have different motor power or pumping capacity. In this study, all the pumps have the same capacity. As for the input variable "total number of open gates", each gravity gate has the same discharge rate at Yu-Cheng station, which makes no differ-

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ence of the discharge capability for individual gates. "The total number of open gates" can reflect the actual status of discharged water. In this station, water is continuously drained away from the sewerage system by either gravity gates or pumps. The water level of YC 10 and the status of total number of open gates (inputs) could easily identify the amount of running pumps (output).

References Chang, F.J., Chang, K.Y. and Chang, L.C., 2008. Counterpropagation fuzzy-neural network for city flood control system. *Journal of Hydrology*, 358(1-2): 24-34. Chang, L.C. and Chang, F.J., 2001. Intelligent control for modelling of real-time reservoir operation. *Hydrological Processes*, 15(9): 1621-1634.

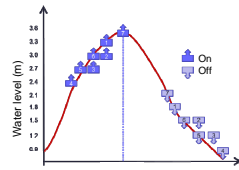
Please also note the supplement to this comment:

<http://www.hydrol-earth-syst-sci-discuss.net/7/C3811/2010/hessd-7-C3811-2010-supplement.pdf>

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Interactive comment on Hydrol. Earth Syst. Sci. Discuss., 7, 6725, 2010.

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The original design of the operating procedure for Yu-Cheng pumping station.

Fig. 1.

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Figure 1 The architecture of CFNN with training procedure.

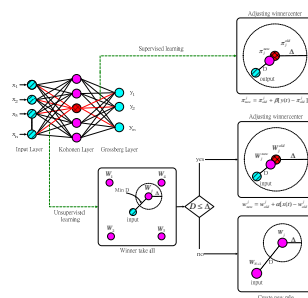


Fig. 2.

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*In Section 2.1.2, I do not understand whether the appropriateness of the Gaussian membership function is checked in some way, in comparison with alternative solutions.*

Response:

For calculating the degree of membership, the Gaussian function has been frequently suggested in literatures and popularly applied in various fields. Besides, the Gaussian function generally provides a more flexible degree of membership and thus produces more appropriate results than the triangular function based on our previous experiences (Chang and Chang, 2001). Therefore, the Gaussian function was selected to represent the degree of membership (Lines 164-168) defined as follows.

$$M_j(x) = \exp \left[ - \frac{\sum_{i=1}^n (x_i - w_j)^2}{\Delta^2} \right]$$

where  $w_j$  is the center of rule  $j$ ,  $\Delta$  is the width of rule  $j$ , and  $n$  is the number of inputs.

In this study, both center and  $\Delta$  were calibrated during the training phase to find out the optimal values for pumping operations.

**Fig. 3.**