Journal of Hydroscience and Hydraulic Engineering
Vol. 17, No.1 May, 1999, 21-27

IMPROVEMENT OF PUMP OPERATIONS IN A COMBINED SEWER SYSTEM USING GENETIC ALGORITHMS AND FUZZY CONTROL

By

S. Yagi

Setsunan University, Neyagawa, Osaka, Japan

and

S. Shiba

Osaka University, Toyonaka, Osaka, Japan

SYNOPSIS

In the present study, fuzzy logic control and genetic algorithms are applied to achieve improved pump operations in a combined sewer pumping station. Pumping rates are determined by fuzzy inference and fuzzy control rules corresponding to input variables. Genetic algorithms are used to automatically improve the fuzzy control rules through genetic operations such as selection, crossover and mutation. The effects of different fitness functions and learning conditions are investigated using a stormwater runoff model. It is found that current pump operations can be improved by adding the sewer water quality to the input variables; and the improved operations can reduce not only floods in the drainage area but also pollutants discharged into the receiving waters.

INTRODUCTION

Water resources systems in urban areas have become largely expanded and highly complicated; accordingly human operators of water-related facilities are now required to work more skillfully than ever. However to achieve such advanced control is not easy for human operators even though many kinds of observed and predicted hydrological information are available. Therefore it is necessary to provide them with computer-aided control systems.

Artificial intelligence technology, which was born from research on human intelligence, has remarkably progressed in recent years. It involves not only expert systems but also fuzzy theory, neural network, genetic algorithms and so on; and has been applied to a variety of fields. In the field of water resources management, it has been applied, for example, to the control of the discharge rates of reservoirs and the flocculation process of water purification plants; and has succeeded in bringing control performance similar to that of skilled operators.

On the other hand, we have engaged in applying fuzzy theory to the pump operations of combined sewer pumping stations and found that it is an appropriate tool to deal with linguistic knowledge of skilled human operators (Yagi (1), (2)). Hearing from skilled experts is a commonly used method for making fuzzy control rules, but it requires a lot of trial and error efforts, which is enormous especially in case of using many input variables. In the present study, genetic algorithms are applied to the automatic learning of fuzzy control rules; and the improvement of current pump operations is discussed.

COMBINED SEWER PUMPING STATIONS

The main role of pumping stations in combined sewer systems is to prevent floods during rain in the drainage areas. At the same time, pumping rates have to be controlled carefully to avoid floods of the receiving waters and also to reduce the discharge of pollutants into the receiving waters. As shown in Fig. 1, highly polluted inflows at the beginning of rain caused by non-point sources are discharged by sanitary pumps to the next pumping station or the treatment plant. When the sewer water level exceeds a certain value or seems to increase because of heavy rain, storm pumps are started to discharge sewage to the receiving waters. Operators in the pumping stations determine the pumping rates skillfully using their knowledge, experience and intuition under the various conditions of rainfall intensity, sewer water level, river water level and so on. A simplified simulation model for a stormwater runoff system as shown in Fig. 1 is used herein; in which fuzzy control is applied to the operations of storm and sanitary pumps (Yagi (1)).

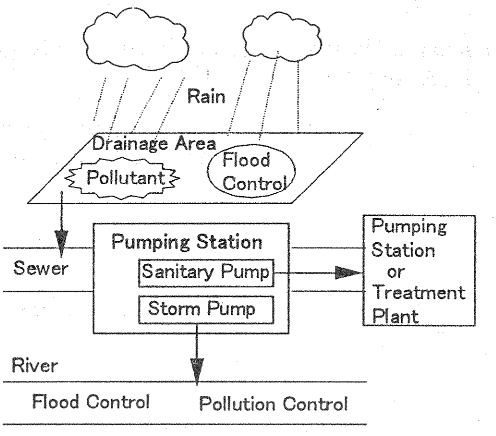

Fig. 1 Stormwater runoff system and pumping stations

FUZZY CONTROL OF PUMPS

Operators' knowledge of pump operations seems to consist of linguistic statements such as "If the sewer water level is very high, then the storm and sanitary pumps should be set at the maximum rates." Fuzzy sets (Zadeh (3)) have been extensively used to deal with such linguistic statements. Fuzzy control methods based on the fuzzy sets have been widely applied to many fields and reported to show performance similar to skilled experts (Sugeno (4)).

Membership Functions of Input and Output Variables

In the present study, input variables of fuzzy control are the rainfall intensity, the sewer water level, the river water level and the sewer water quality; and output variables are storm and sanitary pumping rates. To deal with these variables, nine fuzzy labels having membership functions as shown in Fig. 2 are used: NB, NM, NS, ZE, PS, PM, PB, 11 and 00. X_{min} and X_{max} in Fig. 2 mean the minimum and maximum values of each variable: for example, the rainfall intensity (0 and 50.0 mm/hr), the sewer water level (0.5 and 5.0 m), the river water level (0 and 3.0 m), the sewer water quality (0 and 200 g/m^3), the storm pumps (0 and 8.0 m^3/sec) and the sanitary pumps (0 and 0.67 m^3/sec).

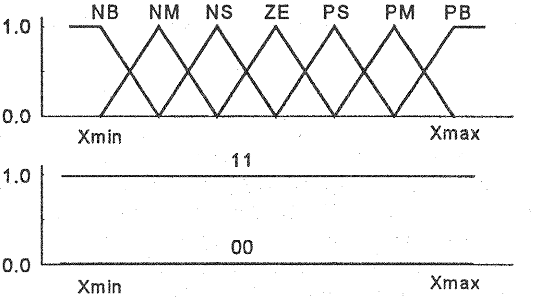

Fig. 2 Membership functions

Fuzzy Control Rules

Fuzzy control rules are expressed in the form of IF - THEN using fuzzy labels as follows.

$$\begin{array}{llll} \text{IF} & X1=PB & X2=PB & \text{THEN } Y=PB \\ \text{IF} & X1=NB & X2=NB & \text{THEN } Y=NB \\ & \cdots & \cdots & \quad\cdots \end{array} \tag{1}$$

where X1, X2, .. = input variables; and Y = output variable. The first rule means "If the sewer water level (X1) is very high (PB) and the rainfall intensity (X2) is very high (PB), then the pumping rate (Y) is the maximum (PB)." Fuzzy labels "11" and "00" shown in Fig. 2 are used in the IF-part and THEN-part, respectively. Therefore, for example, if "X1=11" is involved in a rule, it means that the variable X1 is virtually unnecessary in the rule; and "Y=00" means that the rule is ineffective. This is obvious from the procedure of fuzzy inference as shown below.

Fuzzy Inference

Pumping rates are determined by fuzzy inference responding to input variables such as the rainfall intensity, the sewer water level, and the river water level. Fuzzy inference used here is a so-called min-max-centroid method (Sugeno (4)). In each rule, the minimum value among the memberships of input variables (X1, X2,..) to the fuzzy sets involved in the IF-part is selected as the grade of the rule; then the grade is multiplied to the membership function (Y) of the THEN-part. All these output membership functions of every rule are synthesized by using their maximum values. The centroid of the synthesized membership function is chosen as the output value, namely the pumping rate.

GENETIC ALGORITHMS FOR SEARCHING PREFERABLE FUZZY RULE BASES

Genetic algorithms having a similar process of biological evolution are a kind of optimization method. Solutions are genetically coded and improved to fit the environment through genetic operations such as selection, crossover and mutation (Davis (5), Karr (6), Qian *et al.* (7), Yagi *et al.* (8)).

Genetic Coding of a Fuzzy Rule Base

In the present study, when a fuzzy rule base is shown as

$$\begin{array}{llll} 1: \text{IF} & X1=PB & X2=PS \;\ldots & \text{THEN}\; Y=PB \\ 2: \text{IF} & X1=NB & X2=NS \;\ldots & \text{THEN}\; Y=NB \\ & \ldots & \ldots & \qquad\;\; \ldots \\ N: \text{IF} & X1=ZE & X2=PS \;\ldots & \text{THEN}\; Y=ZE \end{array} \tag{2}$$

it is genetically coded as follows.

$$G_A = \underset{A_1}{(PB,PS,\ldots,PB)}\ \underset{A_2}{(NB,NS,\ldots,NB)}\ \underset{\ldots}{\ldots}\ \underset{A_N}{(ZE,PS,\ldots,ZE)} \tag{3}$$

Fitness Function

A fitness function is used in genetic algorithms to evaluate the degree to which an individual (a fuzzy rule base) fits the environment (control objectives); and is defined here as shown in Table 1 according to the operation type: current and improved.

The fitness function is composed of f_S, f_R and f_L as shown in Fig. 3. In the current operation, the fitness function has a maximum value of 1.0 when pumps are operated to control the maximum sewer water level under 5.0 m and the maximum river water level under 3.0 m. On the other hand, the improved operation is additionally required to reduce the discharged pollutants into the receiving waters.

Table 1 Two types of pump operations

Operation type	Input variable	Control objective and fitness function f
Current operation	- Rainfall intensity - Sewer water level - River water level	- Maximum sewer water level < 5.0 m - Maximum river water level < 3.0 m $f = 0.5 f_S + 0.5 f_R$
Improved operation	- Rainfall intensity - Sewer water level - River water level - Sewer water quality	- Maximum sewer water level < 5.0 m - Maximum river water level < 3.0 m - Discharged pollutant load = 0 g $f = 0.5 f_S + 0.2 f_R + 0.3 f_L$

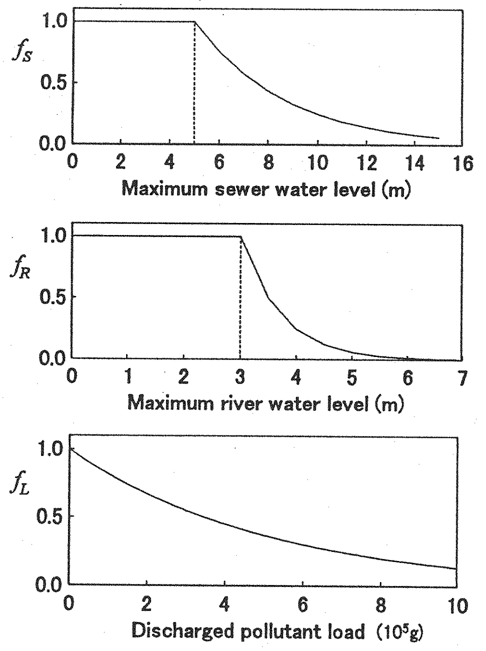

Fig. 3 Elements of fitness functions

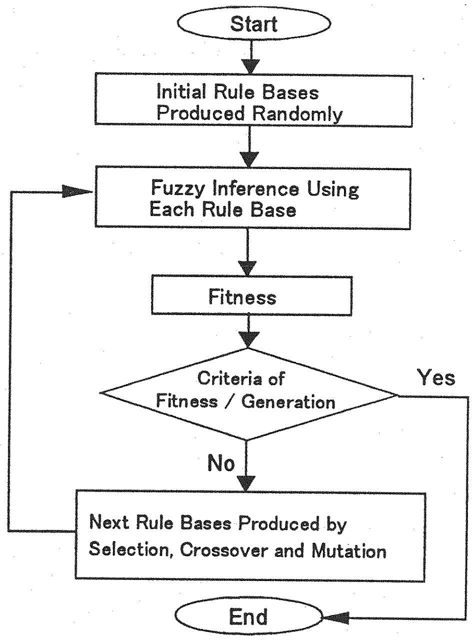

Fig. 4 Flow chart of computation

Genetic Operations

Selection: Selection is an operation in which rule bases are reproduced in the next generation according to their fitness values; among several kinds of selection methods, we used both roulette selection and elite preservation. In the roulette selection, the selection probability of a rule base is determined as a ratio of the fitness value of the rule base to the sum of all the fitness values. By the elite preservation, a rule base having the maximum fitness value is reproduced in the next generation without any genetic changes.

Crossover: By a crossover operation, two rule bases are chosen randomly from a population (a group of rule bases) and are cut at the same location determined randomly; after that, parts of rules are exchanged between the two rule bases. Among several types of crossover methods, one point crossover is used herein. For example, two rule bases G_A and G_B are changed by the crossover as follows.

$$\begin{array}{lll} G_A: A_1A_2 | A_3A_4 \ldots A_N & \longrightarrow & G_A': A_1A_2B_3B_4 \ldots B_N \\ G_B: B_1B_2 | B_3B_4 \ldots B_N & \longrightarrow & G_B': B_1B_2A_3A_4 \ldots A_N \end{array} \qquad (4)$$

A crossover rate is defined as the mean frequency of a rule base being changed by crossover in a generation; and is set here as 1.0.

Mutation: Mutation is an operation in which fuzzy labels in the rule bases are replaced randomly with other labels as follows.

$$X2 = PB \rightarrow X2 = PS \qquad (5)$$

A mutation rate is defined as the mean frequency of replacing a fuzzy label with another label in a generation; and is set here as 0.1.

Computation Procedure

The flow chart of searching preferable rule bases is shown in Fig. 4. A population of rule bases at the first generation is produced randomly. Using results obtained by fuzzy inference, the fitness value of each rule base is computed following the fitness function as shown in Table 1. When the best fitness value of the population becomes 1.0 or the generation reaches a certain value, the search is ended. Otherwise, the next population of rule bases is reproduced through the operations of selection, crossover and mutation. By repeating these steps, preferable rule bases are increased in the population and inherited to the next generation.

APPLICATION TO A COMBINED SEWER PUMPING STATION

Learning Process and Results

A rainfall pattern used here is shown in Fig. 5. The duration of rain is fixed as two hours and the peak rainfall intensity R_p is varied between 10 and 40 mm/hr. An example of learning process for R_p=30 mm/hr is shown in Fig. 6. As the learning proceeds, the fitness value increases; the maximum sewer and river water levels are controlled under 5.0 m and 3.0 m respectively, and the discharge of pollutants is reduced.

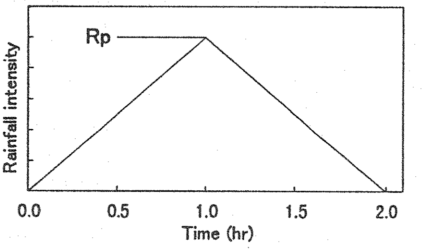

Fig. 5 Rainfall pattern

Figure 7 shows an example of the operations

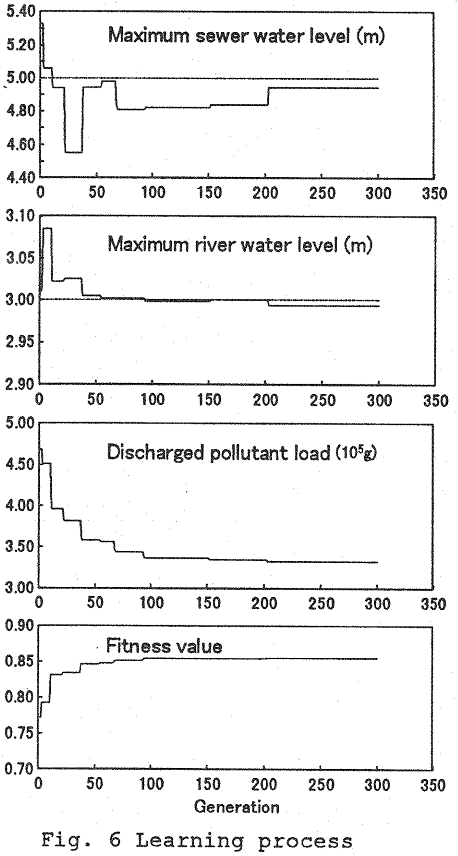

Fig. 6 Learning process

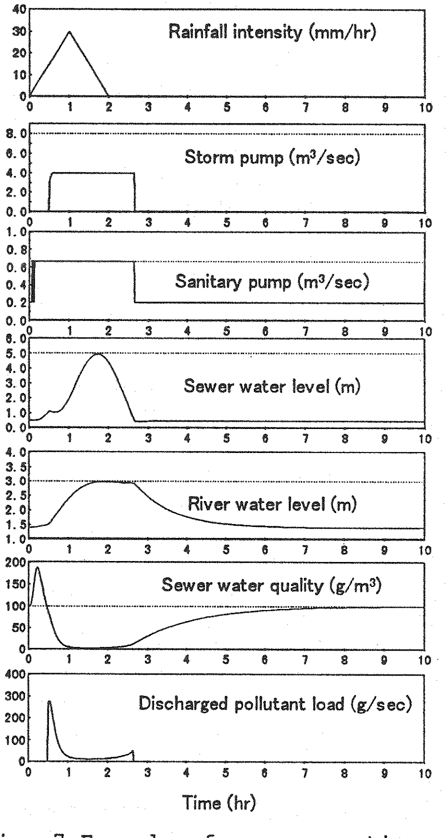

Fig. 7 Example of pump operations

of storm and sanitary pumps using the best rule base obtained by the learning for 300 generations. Highly polluted water at the beginning of rain is discharged to the next pumping station or the treatment plant by sanitary pumps using their maximum capacity (0.67 m^3/sec). Storm pumps are started using about half of the maximum capacity (8.0 m^3/sec) when the sewer water quality becomes low and the sewer water level increases and exceeds about 1.0 m; and are stopped when the sewer water level becomes low and the sewer water quality begins to increase. These features of pump operations seem to be reasonable to achieve the control objectives.

Applicability of Learned Rule Bases

The applicability of a rule base, which is learned using a rainfall pattern, to other rainfall patterns is tested and is shown by a fitness value in Table 2. In case

Table 2 Applicability of learned rule bases

Peak rainfall intensity Rp(mm/hr)		Learning condition				
		10	20	30	40	10,20,30,40
Testing condition	10	*1.00*	*1.00*	0.84	0.87	*1.00*
	15	0.82	0.95	0.87	0.86	0.87
	20	0.67	*0.92*	0.86	0.79	*0.90*
	25	0.59	0.76	0.86	0.85	0.88
	30	0.54	0.55	*0.85*	0.78	*0.86*
	35	0.52	0.45	0.64	0.70	0.71
	40	0.51	0.40	0.56	*0.74*	*0.71*
Mean fitness value		0.67	0.72	0.79	0.80	0.85

*Italics show the fitness values of learned rule bases for the testing conditions.

of a learning condition, R_p=10 mm/hr, the applicability of the rule base to each testing condition of R_p=15, 20,..., 40 mm/hr is resulted in the fitness value of 0.82, 0.67,..., 0.51 respectively and the mean fitness value is 0.67. As the peak rainfall intensity R_p used for learning increases, the mean fitness value becomes higher. A case of learning condition having four rainfall patterns, R_p=10, 20, 30, 40 mm/hr, is also shown in Table 2. The applicability of this case is higher than other cases using one rainfall pattern. Therefore it is necessary to use a variety of learning condition to enhance the applicability of learned rule bases.

Improvement of Current Pump Operations

A current operation is defined here as shown in Table 1; the rainfall intensity, the sewer water level and the river water level are used as the input variables and its control objectives are the prevention of floods in the sewer and the river. On the other hand, an improved operation has the additional objective of reducing discharged pollutants into the receiving waters (river) by adding information of the sewer water quality to the input variables. The results of both operations, which use the rule bases learned with the four rainfall patterns during 300 generations, are shown in Fig. 8.

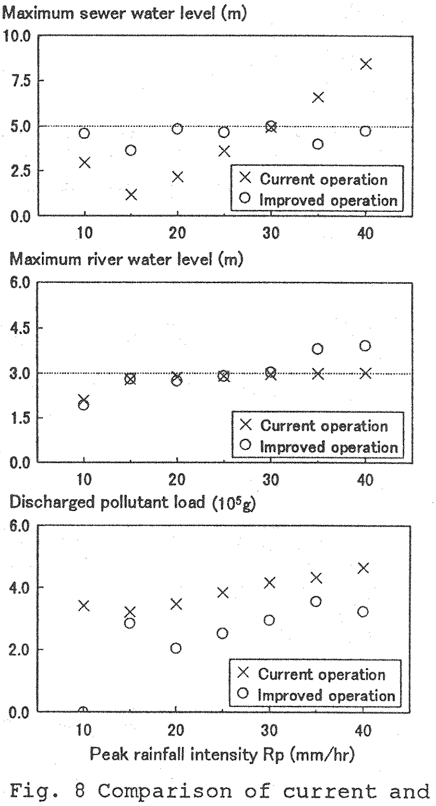

Fig. 8 Comparison of current and improved operations

In case of R_p less than 30 mm/hr, the maximum sewer and river water levels are controlled under 5.0 m and 3.0 m respectively by both operations. However the discharged pollutants of the improved pump operations are less than the current operations. This is due to the improved operations in which highly polluted water at the beginning of rain is discharged only by sanitary pumps using their maximum capacity. Even in case of R_p over 30 mm/hr, the maximum sewer water levels and the discharged pollutants are better controlled by the improved operations than the current operations.

Accordingly we can conclude that the current pump operations can be improved by adding the sewer water quality to the input variables and the reduction of discharged pollutants into the control objectives. Further investigation, however, is needed on the effects of other input variables, the number of rules, and the formulation of the fitness function.

CONCLUSIONS

Using fuzzy logic control and genetic algorithms, a new type of pump operation method for combined sewer pumping stations has been developed. Conclusions are summarized as follows.

Genetic algorithms having operations of selection, crossover and mutation are applied to a combined sewer pumping station and found to be effective in searching reasonable fuzzy rule bases.

The applicability of rule bases increases when the rule bases are learned using a heavier and a wider variety of rainfall patterns.

Current pump operations can be improved by using additional information of the sewer water quality; and the improved operations can reduce not only floods in the drainage area but also pollutants discharged into the receiving waters.

REFERENCES

1. Yagi, S. and M. Kaneko: An application of fuzzy algorithms to the control of pumps in combined sewer systems, Journal of Japan Sewage Works Association, Vol.26, No.303, pp.71-80, 1989 (in Japanese).
2. Yagi, S.: Fuzzy control of pumps in a combined sewer system and its effects on flood and pollution management, Environmental Hydraulics, J. H. Lee & Y. K. Cheung (eds.), Hong Kong, Balkema, pp.1443-1448, 1991.
3. Zadeh, L.A.: Outline of a new approach to the analysis of complex systems and decision processes, IEEE Trans. Systems, Man, and Cybernetics, SMC3 (1), pp.28-44, 1973.
4. Sugeno, M.: Industrial Applications of Fuzzy Control, North-Holland, 1985.
5. Davis, L.: Handbook of Genetic Algorithms, Van Nostrand Reinhold, 1990.
6. Karr, C.L.: Design of an adaptive fuzzy logic controller using a genetic algorithm, Proceedings of the 4th International Conference on Genetic Algorithms, San Diego, pp.450-457, 1991.
7. Qian, Y., P. Tessier and G.A. Dumont: Process modelling and optimization of systems with imprecise and conflicting equations, Engineering Application of Artificial Intelligence, Vol.6, No.1, pp.39-47, 1993.
8. Yagi, S. and M. Kurashiki: Development of a pump operation method for combined sewer systems using genetic algorithms and fuzzy theory, Journal of Japan Sewage Works Association (Research Journal No.17), Vol.34, No.413, pp.84-96, 1997 (in Japanese).

APPENDIX - NOTATION

The following symbols are used in this paper:

A_i	= set of fuzzy labels used in IF-THEN rule i as defined in Eq. 3;
f	= fitness function as defined in Table 1;
f_S, f_R, f_L	= elements of a fitness function, f, as defined in Fig. 3;
G_A	= genetic code of a fuzzy rule base as defined by Eq. 3;
PB,.., NB	= fuzzy labels as defined in Fig. 2;
R_p	= peak rainfall intensity as defined in Fig. 5;
X_{min}, X_{max}	= minimum and maximum values of input variable X;
X1, X2, ..	= input variables of fuzzy control; and
Y	= output variable of fuzzy control.

(Received September 3, 1998 ; revised November 19, 1998)