GA-based Fuzzy Controller Design for Tunnel Ventilation Systems

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Abstract—**The main purpose of tunnel ventilation system is to maintain CO pollutant concentration and VI (visibility index) under an adequate level to provide drivers with comfortable and safe driving environment. Moreover, it is necessary to minimize power consumption used to operate ventilation system. To achieve these purposes, FLC (fuzzy logic controller) has been usually utilized because complex and nonlinear system like tunnel ventilation is difficult to control with conventional quantitative methods. Membership functions of FLC consist of inputs such as pollutant level inside tunnel, pollutant emission rates from vehicles, and outputs, the number of running jet-fans. The conventional fuzzy control methods have been designed just by relying on simple experiences and using trial and error method. In this paper, FLC is optimally redesigned using GA (genetic algorithm) which is a stochastic global search method. In the process of constructing objective function of GA, maintaining pollutant concentration level under allowable limit and decreasing energy consumption are included. Finally, the simulation results performed with real data collected from the target tunnel ventilation system are shown. It is confirmed that the GA-based FLC shows more efficient performance than the conventional FLC.**

Index Terms—**FLC (fuzzy logic controller), real-valued GA (genetic algorithm), tunnel ventilation control.**

I. Introduction

An appropriate operating of roadway tunnel ventilation system provides the drivers passing through the tunnel with comfortable environment and safe driving condition. At the same time, the tunnel ventilation system consumes large amount of energy. So, it is desired to have efficient operating algorithm for the tunnel ventilation in the aspects of safe and comfortable driving environment as well as saving energy. The main target of the roadway tunnel ventilation is to maintain CO pollutant and VI (visibility index) to a certain level. CO is mainly emitted from gasoline passenger cars. The amount of CO pollutant that is over allowable level may cause fatal injury to human body. Generally, 100 ppm is the maximum CO limit that can be allowed [1]. VI is mainly decreased by the smoke emitted from small or large diesel buses and truck. The low VI may considerably decrease drivers' driving capability due to poor visibility.

The most popular control method for tunnel ventilation is FLC (fuzzy logic controller). The pollutants in the tunnel are exhausted from passing vehicles, which are moving sources. Moreover, their transient behavior is characterized with time delay. Due to such problems, complex and nonlinear system like tunnel ventilation is difficult to control with conventional quantitative methods. Nagataki et al. established the foundation of tunnel ventilation system using artificial intelligence [2]. Tamura and Matsushita in [3] and Funabashi et al. in [4] showed computer simulation of FLC making the use of tunnel dynamic model. Koyama et al. applied previous ventilation control methods to real plant [5]. Yoshimochi and Ikebe succeeded the research related to ventilation control with FLC [6][7]. Chen et al. designed performance index for control and evaluated the efficiency of the controller they proposed [1]. Recently, Hong et al. designed a very accurate pollution level estimation algorithm for tunnel system utilizing Kalman filter [8]. The estimated information can be used to develop more efficient control methods for tunnel ventilation.

The control algorithm used in this research is based on FLC. However, the FLC in this paper is not designed just by relying on simple experiences and using trial and error method like the conventional fuzzy control methods listed above. It is reconfigured in the sense of 'optimality' on the base of GA (genetic algorithm). In the process of constructing objective function of GA, maintaining pollutant concentration level under allowable limit is the most important purpose. Besides it, energy consumption is also considerable factor to be included in the objective function. Consequently, GA-based FLC is designed to optimally satisfy both control objectives simultaneously.

This paper is organized as followings. In section Ⅱ, the target system of this research is briefly introduced. In section

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Ⅲ, conventional FLC method is demonstrated and in section Ⅳ, it is presented how FLC can be improved by GA. Then, in section Ⅴ, the simulation results performed with real data collected from the target tunnel ventilation system are shown. It is confirmed that the GA-based FLC shows more efficient performance than the conventional FLC. Finally, the last section contains concluding remarks.

II. TUNNEL VENTILATION SYSTEM

The target tunnel for this research is Dunnae tunnel located in Youngdong highway, Korea. The length, width, and height are 3300 m, 9.2 m, and 7.2 m, respectively. Table. Ⅰ shows the detail specifications of the tunnel. To observe the pollutant levels, CO and VI sensors are arranged to the tunnel with an appropriate interval. Traffic counter equipped at tunnel entrance can measure the number of cars entering into the tunnel. In order to ventilate the pollutants, total 32 jet-fans are installed on the ceiling.

The distribution of pollutants inside tunnel is usually represented with one-dimensional diffusion-advection equation [4]. It has pollutant inputs from passing vehicles as a source term.

$$\frac{\partial c}{\partial t} = \frac{\partial}{\partial x}\left(k\frac{\partial c}{\partial x}\right) - V_w\frac{\partial c}{\partial x} + q \tag{1}$$

In (1), c indicates the pollutant concentration existing inside tunnel. V_w and k are wind velocity and diffusion coefficient, respectively. The first term on the right-hand side explains the diffusion of pollutants and the second term does the advection by the wind. The pollutant source q increases the pollutant level inside the tunnel. However, because the advection and source terms generally dominate the pollutant distribution, the diffusion term is often ignored. Then, the one-dimensional advection equation in which diffusion term is canceled is like following equation.

$$\frac{\partial c}{\partial t} = -V_w\frac{\partial c}{\partial x} + q \tag{2}$$

III. FLC (FUZZY LOGIC CONTROLLER)

Fuzzy controller applied to tunnel ventilation system is composed of three parts like followings.

TABLE I

SPECIFICATIONS OF DUNNAE TUNNEL

Tunnel	Dunnae
Length	3,300 m
Width	9.2 m
Height	7.2 m
Lane	2
Ventilation	Jet-fan

- ***Fuzzification***: transforms input data, pollutant level inside tunnel, and pollutant emission rate by vehicles, into linguistic form.
- ***Inference***: generates fuzzy control input with fuzzy relation and inference rules of fuzzy logic.
- ***Defuzzification***: converts fuzzy value induced in inference part into crisp defuzzified value because fuzzy value cannot be directly used to real control input.

A. Fuzzification

FLC inputs measured by sensor feedback consist of CO

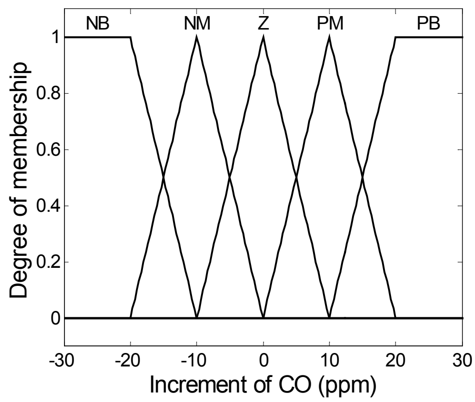

Fig. 1. Membership functions of ΔCO

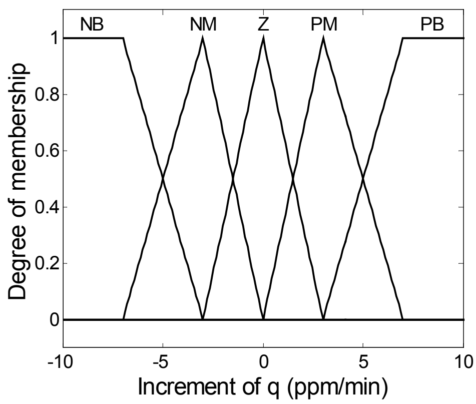

Fig. 2. Membership functions of Δq

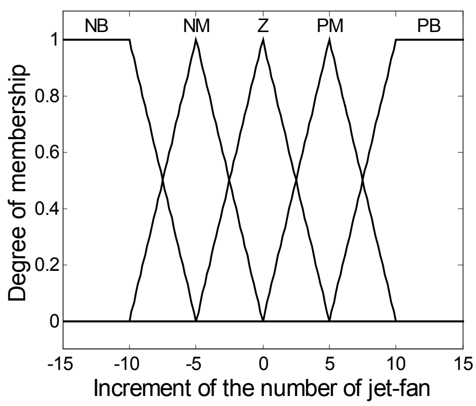

Fig. 3. Membership functions of ΔN_{JF}

pollutant level, VI, and pollutant emission rate by passing vehicles. In order to simplify the descriptions in this paper, only the CO level and pollutant emission rate will be considered in the control design. Adding the VI level to the control algorithm is quite straightforward. The control output of FLC is the increment in the number of running jet-fans. For the purpose of fuzzifing the relationship between inputs and output, the set of fuzzy terminologies is defined like followings: *PB: Positive Big, PM: Positive Medium, Z: Zero, NM: Negative Medium, NB: Negative Big*. The membership functions of the input and output variables are shown from Fig. 1 to Fig. 3.

The first control input of FLC, ΔCO , is the difference of the sensor feedback from the allowable reference CO pollutant level, 40 ppm in this study. q is the pollutant emission rate of CO by vehicles and the second control input Δq is the difference between average reference emission rate and currently observed emission rate. Similarly, ΔN_{JF} , the output of FLC, is the relative number of running jet-fans in tunnel to nominal number in which the jet-fans are operated under the condition of nominal pollutant level. The total number of jet-fans which can be driven is 32, and the nominal number is chosen as 15.

B. Inference

From the membership function graphs shown in from Fig. 1 to Fig. 3, the membership function values about the variation of CO pollutant level and pollutant emission rate by vehicles can be obtained. Then, the control inputs are induced by fuzzy inference rules. Table. Ⅱ represents the FLC inference rules from two fuzzy inputs to the increment of the number of jet-fans. There exist total 17 fuzzy control rules. For example, the rule R_1 and R_2 among the control rules, $R_i(i = 1,2,...,17)$, are expressed as

- R_1 : If ΔCO is *NB*, then ΔN_{JF} is *NB*.
- R_2 : If ΔCO is *NM* and Δq is *NB*, then ΔN_{JF} is *NB*.

where ΔCO and Δq are fuzzy input parameters and ΔN_{JF} is fuzzy output parameter. In this research, 'Max-Min operation rule' proposed by Mamdani in [9] is used in order to infer fuzzy control outputs. With the operation rule, the fuzzy control outputs corresponding to the fuzzy control rules R_1 and R_2 are derived inducing the following equations.

$$RuleOut_1^*(\Delta N_{JF}) = \left[\mu_{\Delta CO(NB)}(x_1)\right] \wedge \mu_{\Delta N_{JF}(NB)}(\Delta N_{JF}) \quad (3)$$

$$RuleOut_2^*(\Delta N_{JF}) = \left[\mu_{\Delta CO(NM)}(x_1) \wedge \mu_{\Delta q(NB)}(x_2)\right] \wedge \mu_{\Delta N_{JF}(NB)}(\Delta N_{JF}) \quad (4)$$

In (3) and (4), $\mu_{\Delta CO}(x_1)$ (or $\mu_{\Delta CO}(x_1)$) is the membership function value when the input of ΔCO (or Δq) is x_1 (or x_2). ΔN_{JF} is the membership function value of fuzzy control output with the number of jet-fans. The final inference result composed of total 17 fuzzy rules is represented by (5).

$$RuleOut^{\circ}(\Delta N_{JF}) = RuleOut_1^*(\Delta N_{JF}) \vee \dots \vee RuleOut_{17}^*(\Delta N_{JF}) \quad (5)$$

C. Defuzzification

$RuleOut^{\circ}(\Delta N_{JF})$ derived from the FLC inference rules cannot be directly applied to real plant as a control input. It is necessary to transform the result to crisp defuzzified value. For this purpose, 'Center of Weight' method is utilized as

$$\Delta N_{JF}{}^{\circ} = \frac{\sum_{i=1}^{17} RuleOut_i^{\circ}(\Delta N_{JF}) \cdot \Delta N_{JF}}{\sum_{i=1}^{17} RuleOut_i^{\circ}(\Delta N_{JF})} \quad (6)$$

where the control input to the real plant is the increment or decrement from the nominal number of running jet-fans, 15.

IV. REAL-VALUED GA (GENETIC ALGORITM)

The GA is a stochastic global search method that imitates the purpose of natural biological evolution. The GA fundamentally includes three operators, selection, crossover, and mutation. The selection operator selects the fittest chromosomes to objective function in order to reproduce the population of approximate solutions. The crossover operator exchanges two chromosomes chosen from the population and creates two offsprings. And the mutation operator randomly transforms a few chromosomes to prevent chromosome population from converging local minimum. A cycle of GA is based on these three processes and iterates from hundreds of times to thousands of times. As the cycles iterate, GA reproduces the population of approximate solutions which are fitter and fitter to objective function.

In conventional fuzzy control, membership functions are

TABLE Ⅱ
FLC INFERENCE RULES

Rule number	Inputs		Output
	ΔCO	Δq	ΔN_{JF}
1	*NB*		*NB*
2	*NM*	*NM*	*NB*
3	*NM*	*NM*	*NM*
4	*NM*	*Z*	*NM*
5	*NM*	*PM*	*NM*
6	*NM*	*PB*	*Z*
7	*Z*	*NB*	*Z*
8	*Z*	*NM*	*Z*
9	*Z*	*Z*	*Z*
10	*Z*	*PM*	*PM*
11	*Z*	*PB*	*PB*
12	*PM*	*NB*	*PM*
13	*PM*	*NM*	*PM*
14	*PM*	*Z*	*PM*
15	*PM*	*PM*	*PB*
16	*PM*	*PB*	*PB*
17	*PB*		*PB*

determined by expert's experience or trial and error method. So, it is difficult to obtain the optimal control result. In this research, the shape of each membership function is optimized by GA and it causes a superior control performance.

A. Chromosome representation

In this research, real-valued type is used to represent chromosome while most of previous studies depended on binary-coded type. Real-valued chromosome representation offers a number of advantages over binary encoding. For example, binary-valued chromosome should be converted to phenotype to evaluate the fitness about objective function but real-valued type does not need the additive process, so the efficiency of GA is increased. In addition, it generates no loss in precision by discretization to binary or other values.

As referred from Fig. 1 to Fig. 3 in section Ⅲ, the input and output membership functions have triangular shape. The ranges of membership functions and the vertices of triangles correspond to the elements of the real-valued chromosome, which are the design factors. Then, the GA is operated and the optimal chromosome, that is the optimal shape of membership functions, is found.

B. Objective function

Objective function is a main criterion to evaluate each chromosome and an important connection between GA and the system. The objective function reflects the objective to be achieved by controller and a penalty for violating a constraint of the system. In this study, the objective value to be minimized has been constructed with combination of pollutant reduction term as the objective and energy consumption term as the constraint. In (7), the pollutant level over allowable limit (40 ppm) and the energy consumption proportional to the number of running jet-fans are combined with an appropriate weighting factor to formulate a reasonable objective function.

$$objective\ function = \begin{cases} (CO_{current} - CO_{ref}) + K \cdot E_{JF} & ,if\ CO_{current} > CO_{ref} \\ E_{JF} & ,if\ CO_{current} < CO_{ref} \end{cases} \tag{7}$$

$$CO_{ref} = 40\,ppm$$
$$K = weighting\ factor$$
$$E_{JF} = jet-fan\,energy$$

To minimize the objective function designed above, the population of chromosomes is selected and the approximate solutions are iteratively produced by GA.

V. Simulation Results

The control algorithm proposed in this paper is verified with computer simulations performed with real data. The data was gathered from the target system of this research, Dunne Tunnel located in Youngdong highway, Korea. The simulation is based on one-dimensional diffusion-advection equation presented in section Ⅱ. The tunnel model is divided into 3 zones and linear interpolations are used. The purpose of tunnel ventilation system is to maintain CO pollutant concentration under an allowable level. It is simultaneously demanded to reduce power consumption used to operate the ventilation system. So, each

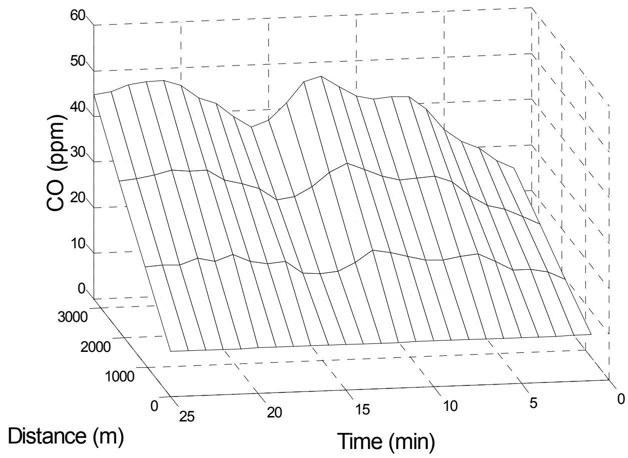

Fig. 4. CO pollutant distribution without control input.

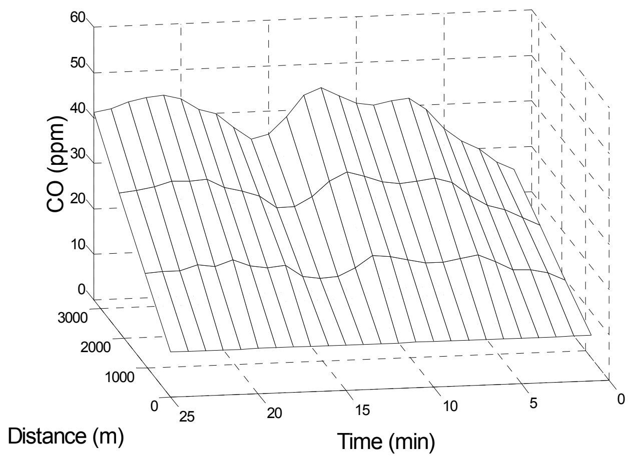

Fig. 5. CO pollutant distribution with pure fuzzy control input.

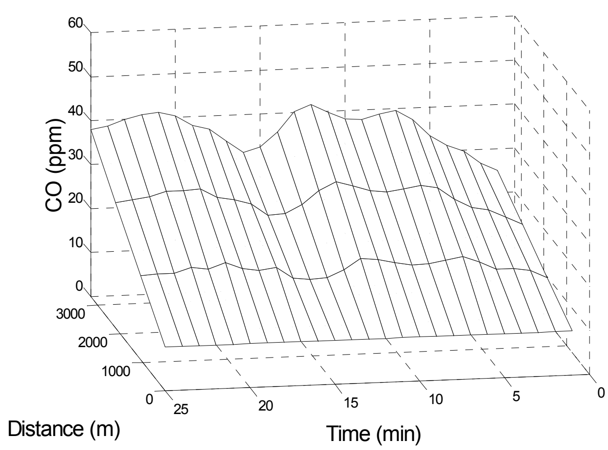

Fig. 6. CO pollutant distribution with modified fuzzy control input using trial-error method.

control algorithm to be introduced hereafter is evaluated with respect to obtaining the two control objectives. This study compares following three cases.

- ***Case 1 : case without control input***
- ***Case 2 : case with fuzzy control input***
- ***Case 3 : case with optimized fuzzy control input using GA***

Among these cases, *Case 2* is classified into fuzzy control with simple and symmetric membership functions used in conventional studies and fuzzy control with intentionally modified membership functions. And the result of the two fuzzy controls is compared each other.

To show the CO pollutant distribution of each section along the tunnel, 3D plots of CO pollutant level about time and distance are described. Fig. 4 shows the pollutant distribution inside the tunnel of *Case 1* in which pollutant emission by passing vehicles is the only input source to the system. In other words, any control input, that is the operation of jet-fans, is not implemented to ventilate the tunnel. In this case, it is shown that the maximum CO pollutant level considerably exceeds 40 ppm, the control objective.

If a control input based on the membership functions and fuzzy rules referred to section 3 is added to the system, pollutant concentration decreases like Fig. 5, which is *Case 2*. In spite of the fuzzy control input, the reduced amount of pollutant cannot meet a desired performance. It means that applying simple symmetric shapes of membership functions and fuzzy rules by intuition hardly achieves the effective pollutant reduction.

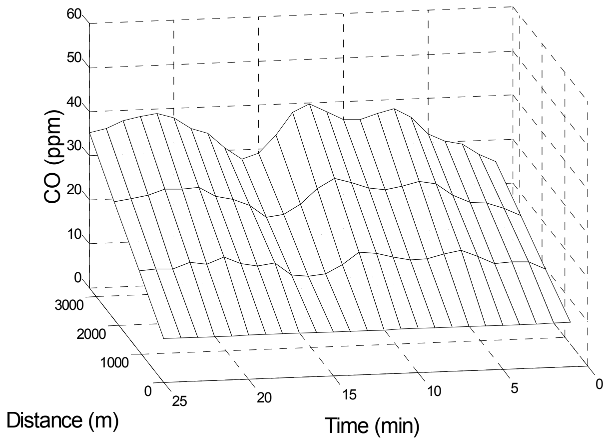

Fig. 7. CO pollutant distribution with fuzzy control input using GA when K = 0.

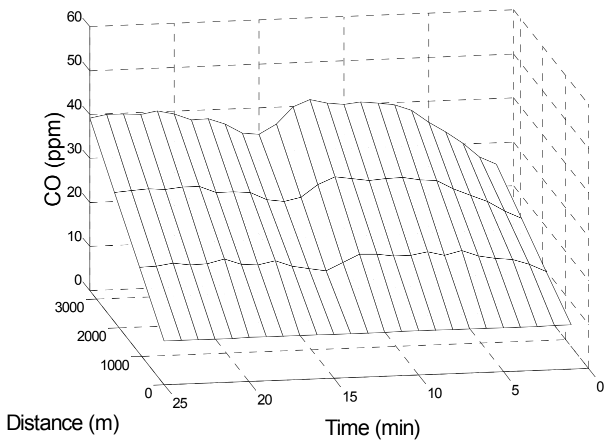

Fig. 8. CO pollutant distribution with fuzzy control input using GA when K = 0.1.

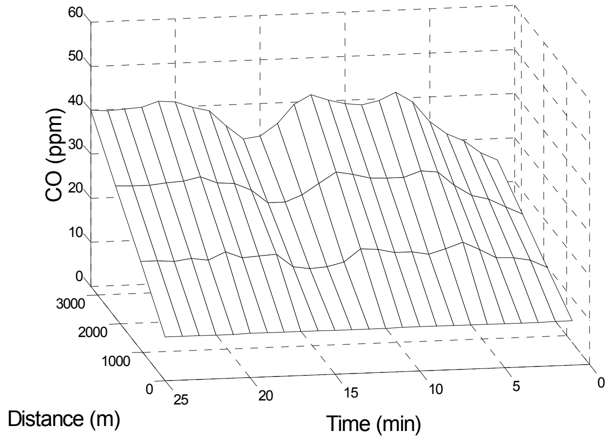

Fig. 9. CO pollutant distribution with fuzzy control input using GA when K = 0.2.

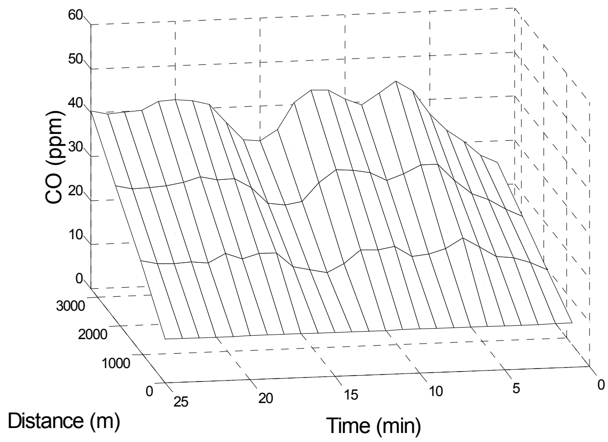

Fig. 10. CO pollutant distribution with fuzzy control input using GA when K = 0.3.

To overcome the problem, membership functions must be reconstructed by trial and error method and several times of simulation should be iterated until a sufficiently acceptable result appears. Though CO pollutant level is diminished through such method as above, it is difficult to know whether the energy consumption is appropriately restricted. The reason why such result appears is like that the amount of consumed energy is possibly diverse due to the different construction of membership functions even though control performance indicates similar quantities of pollutant reduction. Fig. 6 is an example of a decreased pollutant distribution by adjusting the membership functions with trial and error method.

In *Case 3*, GA is applied to attain an optimal performance satisfying pollutant minimization and energy reduction. The results of fuzzy control with membership functions designed by GA is shown from Fig. 7 to Fig. 10. In the process of operating

TABLE Ⅲ
MAXIMUM EXCESSIVE CO POLLUTANT AND ENERGY CONSUMPTION OF EACH CONTROL CASE ACCORDING TO OBJECTIVE FUNCTION WEIGHTING FACTORS

		K	Excessive CO pollutant (ppm)	Energy consumption (kWh)
Without control input			7.258	1094
Fuzzy control without GA	Pure MF		5.577	1207
	Modified MF		1.229	1705
Fuzzy control with GA		0	0	2093
		0.1	1.382	1406
		0.2	1.578	1493
		0.3	4.548	1133

MF = membership function

GA, various weighting factors K between the two control objectives in (7) are implemented. When the weighting factor K is small, pollutant minimization is more dominant over energy reduction. Therefore, GA searches membership functions that minimize much amount of pollutant concentration with relatively large energy consumption. On the contrary, if K has a high magnitude, GA finds membership functions leading to less energy consumption with rather slight effect of pollutant decrement.

Table. Ⅲ compares maximum excessive CO pollutant over allowable level and energy consumption of each control case. As the magnitude of K rises, the importance for reduction of energy consumption grows relatively bigger in implementing GA. In the result, the energy consumption by driving jet-fans is gradually decreasing. However, when K is greater than 0.3, the effect of energy reduction gets too big and the objective of pollutant reduction cannot be sufficiently achieved compared to the case without control input.

Meanwhile, Fig. 6 shows a plot of decreased CO pollutant by intentionally modifying fuzzy controller with trial and error method. Compared to Fig. 8 or Fig. 9, it has a similar effect in the aspect of pollutant reduction but inferior effect in the efficiency of energy reduction. Therefore, fuzzy control with GA has superior performance to others.

VI. CONCLUDING REMARKS

As the pollutant behavior in roadway tunnel is very complicated and has highly nonlinear characteristics, it is quite difficult to efficiently control the ventilation system only with conventional algorithms. So, the ventilation control methods using FLC have been focused by many researchers. The performance of FLC depends on determining fuzzy control rules and selecting appropriate membership functions. However, most studies decided them relying on researcher's experience or previous studies. In this research, the ranges of membership functions were optimally determined to obtain two objectives by GA. The first is to decrease the pollutant level under allowable pollutant limit and the second is to minimize the energy consumed to operate the ventilation system. It was proved that the GA-based fuzzy controller proposed by this study has better performance than previous FLC.

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