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Automation in Construction 17 (2008) 130 – 136

AUTOMATION IN CONSTRUCTION

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GA-based fuzzy controller design for tunnel ventilation systems

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Abstract

The main purpose of a tunnel ventilation system is to maintain CO pollutant concentration and visibility index (VI) under an adequate level to provide drivers with a comfortable and safe driving environment. Moreover, it is necessary to minimize power consumption used to operate the ventilation system. To achieve the objectives, fuzzy control (FLC) methods have been usually utilized due to the complex and nonlinear behavior of the system. The membership functions of the FLC consist of the inputs such as the pollutant level inside the tunnel, the pollutant emitted from passing vehicles, and the output such as the number of running jet-fans. Conventional fuzzy control methods rely on simple experiences and trial and error methods. In this paper, the FLC was optimally redesigned using the genetic algorithm (GA), which is a stochastic global search method. In the process of constructing the objective function of GA, two objectives listed above were included: maintaining an adequate level of the pollutants and minimizing power consumption. The results of extensive simulations performed with real data collected from existing tunnel ventilation system are provided in this paper. It was demonstrated that with the developed controller, the pollutant level inside the tunnel was well maintained near the allowable limit and the energy efficiency was improved compared to conventional control schemes.

Keywords: Tunnel ventilation control; Fuzzy logic controller (FLC); Real-valued genetic algorithm (GA)

1. Introduction

An appropriate operating of a roadway tunnel ventilation system provides the drivers passing through the tunnel with a comfortable environment and safe driving conditions. However, the tunnel ventilation system consumes a large amount of energy. Hence, it is desired to have an efficient operating algorithm for the tunnel ventilation in the aspects of a safe and comfortable driving environment as well as energy saving. The main target of the roadway tunnel ventilation is to maintain CO pollutant and visibility index (VI) to a certain level. CO pollutant is mainly emitted from gasoline-powered passenger cars. The amount of CO pollutant over an 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 diesel buses and trucks. The low VI may considerably decrease the safety of the drivers due to the poor visibility, which may lead to traffic accidents.

The pollutants in the tunnel are exhausted from passing vehicles, which are the moving sources. Moreover, their transient behavior is characterized with a time delay. Such complex and nonlinear characteristics make it difficult to control the ventilation system with conventional quantitative methods. In this respect, the most popular control method for the ventilation systems has been fuzzy logic control. There have been many studies for tunnel ventilation control using fuzzy logic. Tunnel ventilation control system using artificial intelligence was introduced [2] and various experiments on tunnel ventilation control were conducted [3]. Fuzzy model based control scheme was devised [4] and lots of ventilation techniques using fuzzy logic were designed thereafter [5,6]. Saving energy effect by road tunnel ventilation control system was also researched [7]. Moreover, there was a study for evaluating the efficiency of tunnel ventilation controller, using a class of performance index [1]. Recently, a very accurate pollution level estimation algorithm for tunnel system utilizing Kalman

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doi:10.1016/j.autcon.2007.05.011

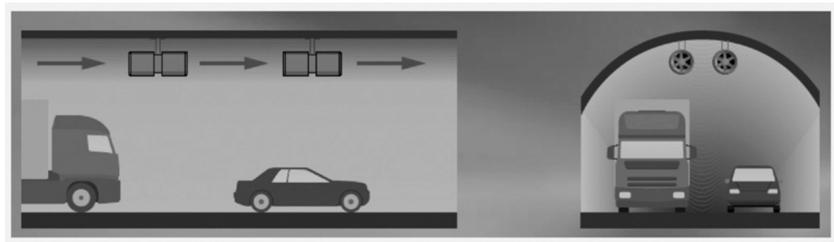

Fig. 1. Schematic diagram of Dunnae tunnel with jet-fans.

filter was designed [8]. The estimated information can be used to develop more efficient control methods for tunnel ventilation.

In this paper, a systematic method for generating membership functions is pursued for optimal fuzzy logic control based on the genetic algorithm (GA). Two main considerations are translated into the objective function for the GA, which include the pollutant concentration level and energy efficiency. A GA-based fuzzy controller is designed to optimally satisfy the objectives.

This paper is organized as follows. In Section 2, the target system for this research is briefly introduced. In Section 3, a conventional fuzzy logic control method is described. Section 4 presents how FLC can be improved by GA. The simulation results are discussed in Section 5, which is followed by some concluding remarks in the last section.

2. Tunnel ventilation system

The Dunnae Tunnel located on Youngdong highway in Korea was selected as the target system for this study. Fig. 1 and Table 1 show a schematic diagram and detailed specifications of the tunnel, respectively. To observe the pollutant levels, CO and VI sensors were installed inside the tunnel in an appropriate interval. The traffic counter located at the tunnel entrance records the number of cars entering the tunnel. In order to ventilate the pollutants, a total of 32 jet-fans were installed on the ceiling.

The distribution of the pollutants inside the tunnel is usually expressed as a one-dimensional diffusion-advection equation [4],

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

where c is the pollutant concentration, V_{w} is the wind velocity and k is the diffusion coefficient. The first term on the right-hand side explains the diffusion of the pollutants and the second term does the advection by 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 can be rewritten as

$$\frac{\partial c}{\partial t} = -V_{\mathrm{w}}\frac{\partial c}{\partial x} + q \tag{2}$$

In order to estimate the change in pollutant distribution, it is necessary to identify the wind velocity inside the tunnel. It can be calculated by the force balance equation, which is expressed as

$$\begin{aligned} &\rho AL\frac{\mathrm{d}V_{\mathrm{w}}}{\mathrm{d}t} = \sum F \\ &\sum F = F_t + F_j + F_r + F_n \end{aligned} \tag{3}$$

where $\sum F$ is the summation of the forces that affect the wind in its flow velocity inside the tunnel [9]. F_t is the traffic ventilation force by passing vehicles, F_j is the equipment ventilation force by jet-fan operation, F_r denotes the wall friction resistance and fluent loss at the entrance and exit, and F_n explains the wind resistance by the natural wind outside the tunnel. Besides, ρ is the density of air, A is the cross-sectional area of the tunnel, and L is the longitudinal length of the tunnel.

Table 1
Specifications of Dunnae tunnel

Tunnel	Dunnae
Length	3300 m
Width	9.2 m
Height	7.2 m
Lane	2
Cross-sectional area	65.65 m^2
Ventilation	Jet-fan type

3. Fuzzy logic controller (FLC)

The fuzzy logic controller applied to the tunnel ventilation system is composed of three parts as follows.

— Fuzzification: transformation of the input data, pollutant level, and pollutant emission rate to a linguistic form.
— Inference: generation of a fuzzy control input based on fuzzy relations and inference rules.
— Defuzzification: convertion of fuzzy values induced in the inference into crisp defuzzified values.

3.1. Fuzzification

The FLC inputs include the CO pollutant level, VI, and pollutant emission rate to be measured. In this paper, only the CO level and pollutant emission rates are considered in the controller design. It is noted that adding a VI level to the control algorithm is quite straightforward. The output of the FLC is an

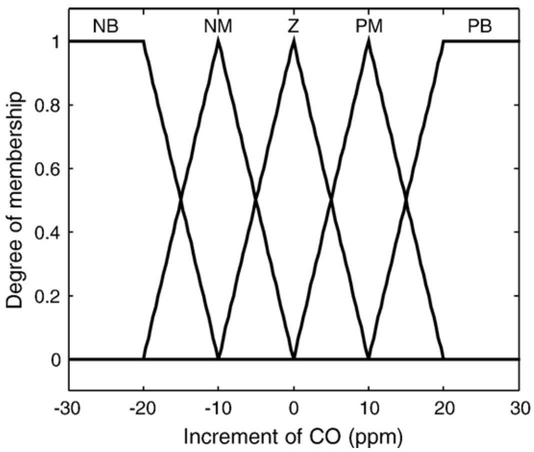

Fig. 2. Membership functions of ΔCO.

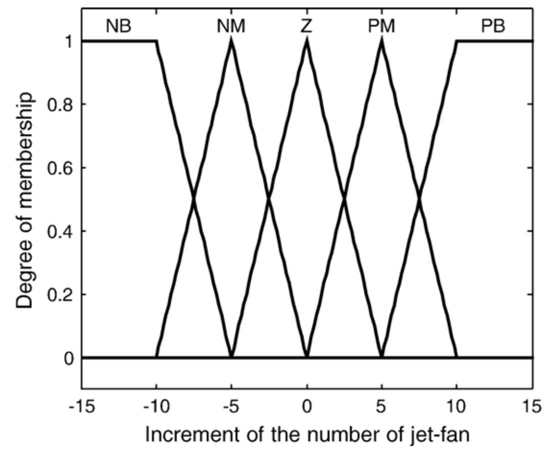

Fig. 4. Membership functions of ΔN_{JF}.

increment of the number of the jet-fans to be activated. For the purpose of fuzzifying the relationship between the inputs and outputs, a set of fuzzy terminologies is defined as follows: PB: Positive Big, PM: Positive Medium, Z: Zero, NM: Negative Medium and NB: Negative Big. The membership functions of the input and output variables are shown in Figs. 2–4.

The first control input ΔCO, is the difference of the measured CO and the reference CO pollutant level, 40 ppm in this study. q is the pollutant emission rate and the second control input Δq is the difference of the average reference emission and observed emission rates. Similarly, ΔN_{JF}, the output of FLC, is the relative number of the running jet-fans to the nominal number of which the jet-fans are operated under the condition of the nominal pollutant level. The total number of the jet-fans to run is 32, and the nominal number is chosen to be 15.

3.2. Inference

From the membership function graphs shown in Figs. 2–4, the membership function values for the variation of the CO pollutant level, the pollutant emission rate, and the number of jet-fans can be obtained. Then, the control outputs are induced by the fuzzy inference rules. Table 2 shows the FLC inference rules for two fuzzy inputs to the increment of the number of jet-fans. There exists the total of 17 fuzzy control rules. For example, the rules R_1 and R_2 are expressed as

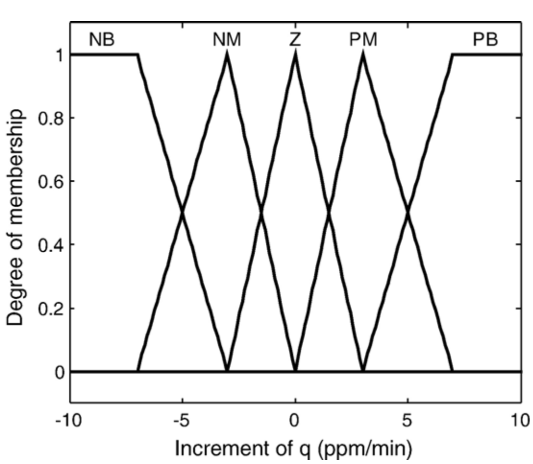

Fig. 3. Membership functions of Δq.

— 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 the fuzzy input parameters and ΔN_{JF} is the fuzzy output parameter. The "Max–Min operation rule" proposed by Mamdani in [10] is used in order to infer the fuzzy control outputs. With the operation rules, the fuzzy control outputs corresponding to the fuzzy control rules R_1 and R_2 are derived as

$$\mathrm{RuleOut}_1^*(\Delta N_{\mathrm{JF}}) = [\mu_{\Delta\mathrm{CO(NB)}}(x_1)] \wedge \mu_{\Delta N_{\mathrm{JF}}(\mathrm{NB})}(\Delta N_{\mathrm{JF}}) \quad (4)$$

$$\mathrm{RuleOut}_2^*(\Delta N_{\mathrm{JF}}) = [\mu_{\Delta\mathrm{CO(NM)}}(x_1) \wedge \mu_{\Delta q(\mathrm{NB})}(x_2)] \wedge \mu_{\Delta N_{\mathrm{JF}}(\mathrm{NB})}(\Delta N_{\mathrm{JF}}) \quad (5)$$

where ∧ is a logical operator, i.e., $a \wedge b = \min(a, b)$.

Table 2
FLC inference rules

Rule number	Input1	Input2	Output
	ΔCO	Δq	ΔN_{JF}
1	NB		NB
2	NM	NB	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

In Eqs. (4) and (5), $\mu_{\Delta\mathrm{CO}}(x_1)$ (or $\mu_{\Delta q}(x_2)$) is the membership function value when the input of ΔCO (or Δq) is x_1 (or x_2). $\mu_{\Delta N_{\mathrm{JF}}(\mathrm{NB})}(\Delta N_{\mathrm{JF}})$ is the membership function value of the fuzzy control output with the number of the jet-fans. The final inference result composed of the fuzzy rules is written as

$$\mathrm{RuleOut}^{\mathrm{o}}(\Delta N_{\mathrm{JF}}) = \mathrm{RuleOut}_1^{*}(\Delta N_{\mathrm{JF}}) \vee \ldots \vee \mathrm{RuleOut}_{17}^{*}(\Delta N_{\mathrm{JF}}) \tag{6}$$

where $\vee$ is a logical operator, i.e., $a \vee b = \max(a, b)$.

3.3. Defuzzification

$\mathrm{RuleOut}^{\mathrm{o}}$ (ΔN_{JF}) derived from the FLC inference rules cannot be directly applied to the real plant as a control command. Therefore, it is necessary to transform the result to a crisp defuzzified value. For this purpose, the "Center of Weight" method is utilized as following:

$$\Delta N_{\mathrm{JF}}{}^{\circ} = \frac{\sum_{i=1}^{17} \mathrm{RuleOut}_i^{\mathrm{o}}(\Delta N_{\mathrm{JF}}) \cdot \Delta N_{\mathrm{JF}}}{\sum_{i=1}^{17} \mathrm{RuleOut}_i^{\mathrm{o}}(\Delta N_{\mathrm{JF}})} \tag{7}$$

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

4. Real-valued genetic algorithm (GA)

The genetic algorithm (GA) is a stochastic global search method that implements the process of natural biological evolution. The GA employs three different operators: *selection*, *crossover*, and *mutation*. The *selection* operator selects the fittest chromosomes to an 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 the chromosome population from converging local minimum. A cycle of the GA is based on these three processes and iterates from hundreds of times to thousands of times. As the cycles iterate, the GA reproduces the population of approximate solutions which are fitter and fitter to the objective function.

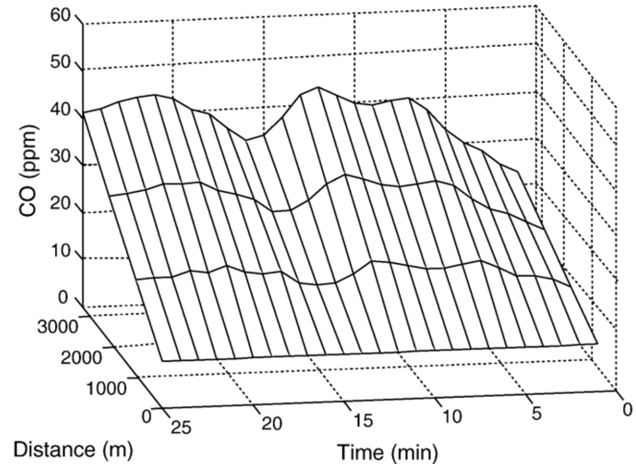

Fig. 6. CO pollutant distribution with pure fuzzy control input.

In a conventional fuzzy control method, the membership functions are determined by an expert's experience or a trial and error method, which makes it difficult to obtain an optimal performance. In this paper, the shape of each membership function is optimized by the GA, which is expected to produce a desirable control performance.

4.1. Chromosome representation

A real-valued type is used to represent the chromosome while most of the previous studies depend on a binary-coded type. The real-valued chromosome representation offers a number of advantages over the binary encoding. For example, the binary-valued chromosome should be converted to a phenotype so as to evaluate the fitness. However, the real-valued type does not need the additive process, which increases

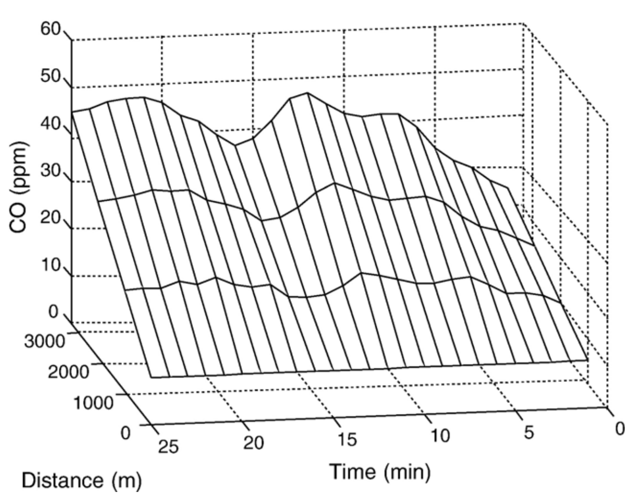

Fig. 5. CO pollutant distribution without control input.

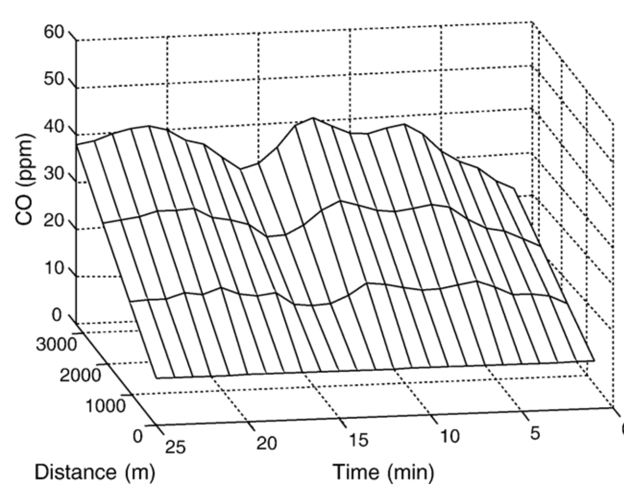

Fig. 7. CO pollutant distribution with modified fuzzy control input using trial and error method.

the efficiency of the GA. In addition, there is no loss in precision by discretization to binary or other values.

As shown in Figs. 2–4, the input and output membership functions have triangular shapes. The ranges of the membership functions and the vertices of the triangles correspond to the elements of the real-valued chromosome as the design factors. Then, the GA is executed to find an optimal chromosome as the optimal shape of membership functions.

4.2. Objective function

The objective function is the main criterion to evaluate each chromosome and an important connection between the GA and the system. The objective function reflects the objectives to be achieved by the controller and a penalty for violating a constraint of the system. In this paper, the objective function to be minimized has been constructed by combining the pollutant reduction term as the objective and the energy consumption term as the constraint. In Eq. (8), the pollutant level above an allowable limit and the energy consumption proportional to the number of running jet-fans are combined with an appropriate weighting factor, K.

$$\text{objective function} = \begin{cases} (\mathrm{CO}_{\mathrm{current}} - \mathrm{CO}_{\mathrm{ref}}) + K \cdot E_{\mathrm{JF}}, & \text{if } \mathrm{CO}_{\mathrm{current}} > \mathrm{CO}_{\mathrm{ref}} \\ E_{\mathrm{JF}} & , \text{if } \mathrm{CO}_{\mathrm{current}} < \mathrm{CO}_{\mathrm{ref}} \end{cases} \tag{8}$$

where $\mathrm{CO}_{\mathrm{ref}}$ is the reference CO pollutant level of 40 ppm, $\mathrm{CO}_{\mathrm{current}}$ is the current CO sensor feedback, and E_{JF} is the energy consumed by the operation of the jet-fans. To minimize the objective function, the population of the chromosomes is selected and the approximate solutions are iteratively produced by the GA.

5. Simulation results

The proposed control algorithm was verified with computer simulations performed with real data. The data for the simulation study were gathered from a real tunnel system,

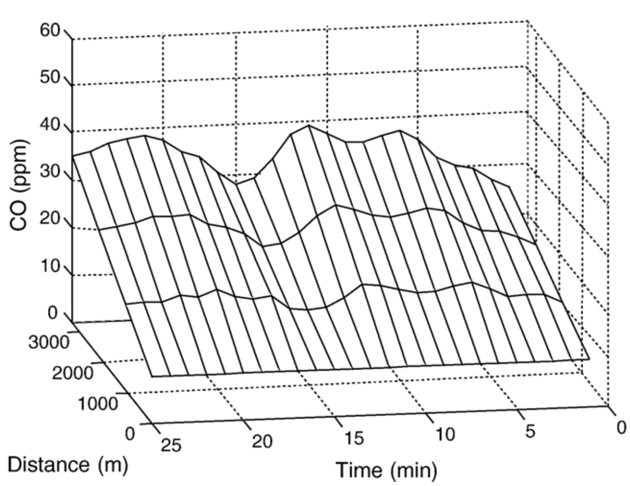

Fig. 8. CO pollutant distribution with fuzzy control input using GA when $K=0$.

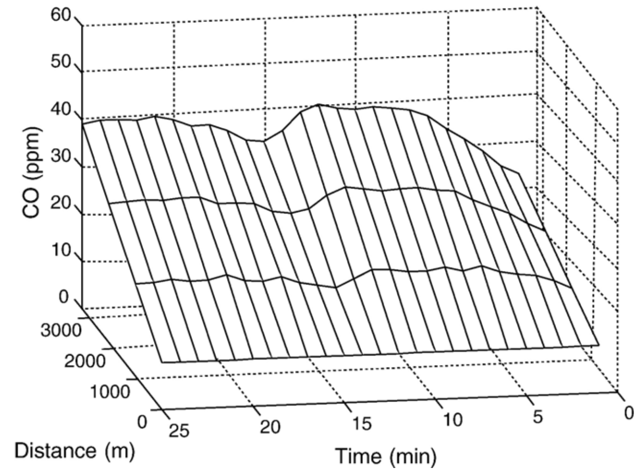

Fig. 9. CO pollutant distribution with fuzzy control input using GA when $K=0.1$.

Dunne Tunnel located in Youngdong highway, Korea. The simulation was based on Eq. (2), one-dimensional advection equation. Linear interpolations were performed to divide the tunnel model into 3 different zones. The purpose of a tunnel ventilation system is to maintain the CO pollutant concentration under an allowable level. It is also intended to reduce the energy cost to operate the ventilation system. Hence, each control algorithm to be introduced hereafter is evaluated with respect to achieving the two control objectives. This study compares the 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 devided into two more detailed examples again. The one is a fuzzy control with simple and symmetric membership functions used in conventional studies. And the other is a fuzzy control with intentionally modified

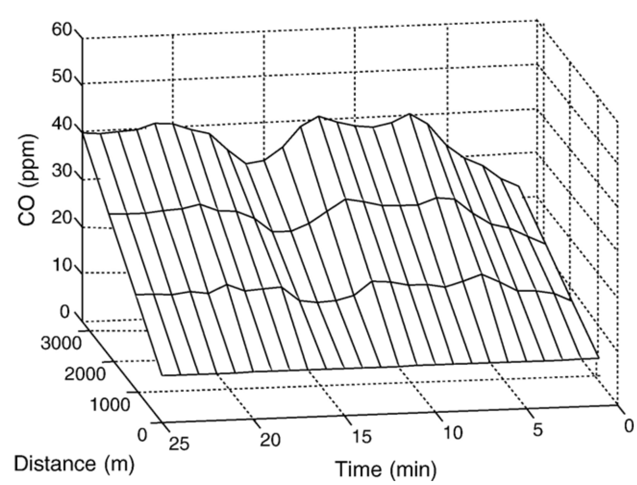

Fig. 10. CO pollutant distribution with fuzzy control input using GA when $K=0.2$.

membership functions to obtain the objective of the system by a trial and error method.

To show the CO pollutant distribution of each section of the tunnel, 3D plots of the CO pollutant level in terms of time and distance are described. Fig. 5 shows the pollutant distribution along the longitudinal distance of the tunnel in Case 1. The pollutant emission by passing vehicles is the only input source for the system. In other words, any control input except the operation of the nominal number of the jet-fans is not conducted to ventilate the tunnel. As such, it is shown that the maximum CO pollutant level considerably exceeds the reference level of 40 ppm.

In Case 2, if a control input based on the membership functions and fuzzy rules described in Section 3 is added to the system, the pollutant concentration decreases as shown in Fig. 6. In spite of the fuzzy control input, the reduced amount of the pollutant cannot meet the desired performance. It means that applying simple symmetric shapes of the membership functions and fuzzy rules by intuition hardly achieves the effective pollutant reduction. To overcome the problem, the membership functions must be reconstructed by a trial and error method. However, it is difficult to see whether the energy consumption is also properly restricted even with the CO pollutant level diminished through such a tuning procedure. The reason seems to be that the membership functions are tuned manually on a trial and error basis. A significant amount of tuning effort was put into the control design to achieve the objectives. However, the performance of the system, was not satisfactory in the sense that the CO pollutant level was reduced closely to the reference value without reaching the desirable energy efficiency. Fig. 7 shows an example of decreased pollutant distribution by adjusting the membership functions based on a trial and error method without the consideration of energy consumption.

In Case 3, the GA was applied to attain an optimal performance satisfying the objectives of pollutant minimization and energy reduction. The GA replaces the tedious and time-consuming manual tuning and makes the fuzzy controller achieve the two objectives at the same time. The results of fuzzy control with the membership functions designed by the GA can be observed in Figs. 8–11. Different values of the weighting factors K were attempted. When the weighting factor K is low, the pollutant minimization is more dominant than the energy reduction. Therefore, the GA searches the membership functions that minimize the pollutant concentration with relatively large energy consumption. On the contrary, when K is high, the GA finds the membership functions leading to less energy consumption with rather a slight effect of pollutant decrement. However, if the weighting factor is properly selected, i.e., 0.1 or 0.2, the controller efficiently adjusts the number of the jet-fans to be activated so that the CO level is maintained near the allowable limit of 40 ppm. Moreover, if the CO pollutant is maintained well below the allowable limit and an excessive energy is consumed by running unnecessary overworking jet-fans, the controller decreases the number of jet-fans and saves the energy consumption. These two facts, as shown in Figs. 9 and 10, explain that the GA-based fuzzy controller achieves the control objectives with the objective function formulated for the system.

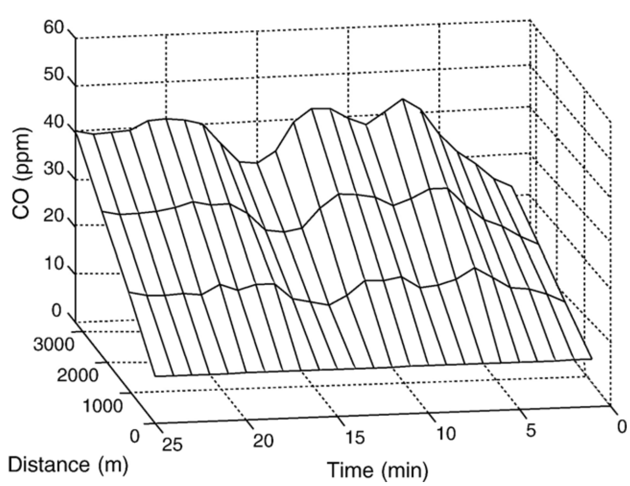

Fig. 11. CO pollutant distribution with fuzzy control input using GA when $K=0.3$.

Table 3
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	179.9
Fuzzy control without GA	Pure MF[a]		5.577	198.5
	Modified MF[a]		1.229	280.4
GA-based fuzzy control		0	0	344.2
		0.1	1.382	231.2
		0.2	1.578	245.6
		0.3	4.548	186.3

[a] MF: membership function.

The performance of the proposed control method is evaluated with respect to the reduction of the CO pollutant level and energy consumption. Table 3 compares the maximum CO pollutant level to the allowable level and the energy consumption of each control case. In the case of GA-based fuzzy control, as the magnitude of K increases, the importance of reducing the energy consumption grows relatively. As a result, the energy consumption decreases gradually. However, when K is greater than 0.3, the effect of energy reduction dominates at the cost of pollution reduction. However, with K set to 0.1 or 0.2, the CO pollutant level stays near the allowable limit and the energy consumption becomes very low, which basically demonstrates the performance of the GA-based fuzzy controller is superior to that of the conventional fuzzy controller.

6. Concluding remarks

In order to control a tunnel ventilation system efficiently, a GA-based fuzzy control method was developed. The objectives of developing a tunnel ventilation system include regulation of the pollutant concentration level under an appropriate limit and minimization of the energy consumption to operate control elements. By incorporating the goals, a tunnel ventilation controller was designed to produce an optimal performance of the system. While the membership functions of the FLC were determined based on personal experiences and trial and error, the ranges of membership functions were optimally determined by the GA. The proposed controller was verified through various simulations and their analyses were performed. An extensive simulation study demonstrated the efficacy of the GA-based fuzzy controller in term of pollutant concentration and energy consumption.

Acknowledgement

This work was performed in part of 2003 industrial-educational cooperation project, 'Underground, Fire, and Environment Research' supported by Korea Institute of Construction and Transportation Technology Evaluation and Planning, and partially supported by the Brain Korea 21 Project in 2006.

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