# Design of FLC for High-Angle-of-Attack Flight Using Adaptive Evolutionary Algorithm

**Tae-Hyun Won***
*Department of Electrical Engineering, Dongeui Institute of Technology, Busan 614-715, Korea*
**Gi-Hyun Hwang, June Ho Park**
*Department of Electrical Engineering, Pusan National University, Busan 609-735, Korea*
**Man Hyung Lee**
*School of Mech. Eng. & ERC/Net Shape and Die Manufacturing, Pusan National University, Busan 609-735, Korea*

In this paper, a new methodology of evolutionary computations - An Adaptive Evolutionary Algorithm (AEA) is proposed. AEA uses a genetic algorithm (GA) and an evolution strategy (ES) in an adaptive manner in order to take merits of two different evolutionary computations : global search capability of GA and local search capability of ES. In the reproduction procedure, the proportions of the population by GA and ES are adaptively modulated according to the fitness. AEA is used for designing fuzzy logic controller (FLC) for a high-angle-of-attack flight system for a super-maneuverable version of F-18 aircraft. AEA is used to determine the membership functions and scaling factors of an FLC. The computer simulation results show that the FLC has met both robustness and performance requirements.

**Key Words :** FLC, High-Angle-of-Attack Flight, AEA, F-18

## 1. Introduction

High-angle-of-attack flight is now relatively an important issue in designing flight control systems for super-maneuvering. Some tactical payoffs of the super-maneuverability can increase first-shot opportunities because of the confusion of adversary pilots. Though super-maneuvers are performed at a low speed without imposing undue load factors to the pilot, the rapid rates of motion can be beyond the pilot's control. Thus a closed loop control of high-angle-of-attack flight is required for both the pilot and the aircraft. Designing such a control system could be further complicated by highly nonlinear aerodynamics during transient motion with large amplitude.

Earlier methods for the high-angle-of-attack flight control system are that a a variable gain scheduling output feedback control (Ostroff, 1992 ; Adams et al., 1994) which provides a class of controller that is super-maneuverable with high performance over a wide operating range. While the earlier methods are nearly the minimum time maneuvers, they probably represent the best controllers based primarily on the linear design methodology in conjunction with somewhat ad-hoc nonlinear corrections. Though the sliding mode has been employed for designing the flight control system, because of its direct applicability to the nonlinear system (Lee and Hedrick, 1994), it cannot lead to the development of the generic high-angle-of-attack flight control methodology because of the redundancy of control effectors such as the elevator and the thrust vectoring nozzle. Consequently, a conventional

* Corresponding Author,
**E-mail** : thwon@dit.ac.kr
**TEL** : +82-51-860-3208; **FAX** : +82-51-860-3327
Department of Electrical Engineering, Dongeui Institute of Technology, Busan 614-715, Korea. (Manuscript **Received** January 28, 2002; **Revised** October 30, 2002)

adaptive control scheme (Cho, 1993) is also limited in generating correct control inputs to the aircraft. In such a situation, the FLC is a promising tool for the high-angle-of-attack flight. However, fuzzy rule and membership functions shape should be adjusted to obtain the best control performance in the FLC (Won et al., 1999). Conventionally it is, as based on the experience of experts and trial and error method, hard to determine membership functions suitable to system without the knowledge of the system. Recently, using evolutionary computations (ECs) which are probabilistic optimal algorithm based on the natural genetics and evolutionary theory, and tuning the membership function shape and fuzzy rules of the FLC with ECs, satisfactory performances is obtained (Zhou and Lai, 2000 ; Juang et al., 2000 ; Shi et al., 1999).

ECs are based on the principles of the genetics and natural selection. There are three broadly similar avenues of investigation in ECs : genetic algorithm (GA), evolution strategy (ES), and evolutionary programming (EP) (Fogel, 1995 ; Goldberg, 1989 ; Gong et al., 1996, Schlierkamp-Voosen and Muhlenbein, 1996 ; Srinivas and Patnaik, 1994 ; Spears, 1995 ; Fogel, 1995 ; Schwefel, 1995 ; Michalewicz, 1992 ; Renders and Flasse, 1996 ; Gen and Cheng, 1997). GA simulates the crossover and mutation of natural systems, performing a global search (Goldberg, 1989), whereas, ES simulates the evolution of an asexually reproducing organism. ES can find a global minimum. If combined with other ECs, it also could be efficient local search technique (Goldberg, 1989).

The performance of ECs is influenced by parameters such as the size of population, the fitness, the probability of crossover and mutation, etc. If these are not adequately selected, the execution time will be longer and premature convergence to local minimum can occur. To solve the above problems several approaches have been proposed. To enhance the performance of GA, population size, the probability of crossover and mutation, and operation method is adaptively modified in each generation (Arabas et al., 1994 ; Schlierkamp-Voosen and Muhlembein, 1996 ; Srinivas and Patnaik, 1994 ; Spears, 1995). To enhance the performances of ES and EP, the mutation parameters are adapted during the run in ES and EP (Goldberg, 1989 ; Fogel et al., 1991 ; Schwefel, 1995 ; Michalewicz, 1992).

In the conventional method described above, parameter values and operator probabilities for the GA and ES are adapted to find solution efficiently. In this paper, however, we propose adaptive evolutionary algorithm (AEA), in which, the ratio of population to which GA and ES will adapt is adaptively modified in reproduction according to the fitness. We use ES to optimize locally, while the GA optimizes globally. In other words, the resulting hybrid scheme produces improves reliability by using the "global" nature of the GA as well as the "local" improvement of the ES. The new AEA is applied to the search for optimal settings of the membership function's shapes and gains of the inputs and outputs of FLC for a high angle of attack flight system for a super-maneuverable version of F-18 aircraft.

## 2. Adaptive Evolutionary Algorithm

### 2.1 Motivation

GA, probabilistic optimization methods, is robust and it is able to solve complex and global optimization problem. But disadvantage is that it can suffer from excessive computation time before providing an accurate solution because of minimal use of prior knowledge and local information (Renders and Flasse, 1996). ES, which simulates the evolution of asexually reproducing organism, has efficient local search capability. Hybrid EC (Gong et al., 1996) is formed to solve complex problem.

In this paper, AEA is designed by combining the GA and ES to reach the global optimum accurately and reliably in a short execution time. In AEA, GA and ES operators are applied simultaneously to the individuals of the present generation to create the next generation. Individuals with a higher fitness value have the higher probability of contributing one or more chromosomes to the next generation. This mechanism gives greater rewards to either GA or ES operation depending on what produces superior offspring.

### 2.2 Adaptive evolutionary algorithm

In AEA, the number of individuals created by the GA and ES operations is changed adaptively. An individual is represented as a real-valued chromosome, which makes it possible to hybridize GA and ES operations.

ES forms a class of optimization techniques motivated by the reproduction of biological system, and the population of individuals evolves toward the better solutions by means of the mutation and selection operation. In this paper, a $(\mu, \lambda)$-ES is adopted. That is, only the $\lambda$ offspring generated by mutation competes for survival, and the $\mu$ parents are completely replaced in each generation. Also, self-adaptive mutation step sizes are used in ES.

For AEA to self-adapt GA and ES operators, each individual has an operator code to determine which operator to use. Suppose a '0' refers to GA, and a '1' to ES. At each generation, if it is more efficient to use the GA, more '0's should appear at the end of individuals. But if it is more efficient to use the ES, more '1's should appear. After reproduction by the roulette wheel selection according to the fitness, GA operations (crossover and mutation) are performed on the individuals that possess the operator code of '0' and the ES operation (mutation) is performed on the individuals that have an operator code of '1'. Elitism is also used. The best individual in the population is reproduced both the GA population and ES population in the next generation. The major procedures of AEA are as follows :

***Initialization*** : The initial population is generated randomly. For each individual, randomly initialize operator code. According to the operator code, GA operations are performed on the individuals with operator code '0', while ES operation is applied where the operator code is '1'.
***Evaluation and Reproduction*** : Using the selection operator, individual chromosomes are selected in proportional to their fitness that is evaluated using an objective function. After reproduction, GA operations are performed on the individuals having an operator code of '0' and the ES operation is performed on the individuals having an operator code '1'. At every generation, the percentages of '1's and '0's in the operator code indicate the performance of the GA and ES operator.
***Preservation of Minimum Number of Individuals*** : At each generation, AEA sometimes may fall into a situation where the percentage of the offspring by one operation is nearly 100%, and the offspring by other operations dies off. Therefore, it is necessary for AEA to preserve certain amount of individuals for each EC operation. In this paper, we randomly change the operator code of the individuals with a higher percentage until the number of individuals for each EC operation become more than a certain amount of individuals to be preserved. The predetermined minimum number of individuals to be preserved is set to 20% of the population size.
***Genetic Algorithm and Evolution Strategy*** : The real-valued coding is used to represent a solution (Michalewicz, 1992 ; Gen and Cheng, 1997). Modified simple crossover and uniform mutation are used as genetic operators. The modified simple crossover operator is the way to generate offs-

< Before Crossover > < After Crossover >

$$S_v^t = [V_1, \dots, V_k, \dots, V_n] \longrightarrow S_v^{t+1} = [V_1, \dots, V_k', V_{k+1}' \dots, V_n']$$

$$S_w^t = [W_1, \dots, W_k, \dots, W_n] \longrightarrow S_w^{t+1} = [W_1, \dots, W_k', W_{k+1}' \dots, W_n']$$

Crossover point

where, $V_j' = a_1 V_j + a_2 W_j$
$W_j' = a_1 W_j + a_2 V_j$
$a_1, a_2$ : Random numbers from [0, 1]
$V_j$ : j-th gene of the vector $S_v$
$W_j$ : j-th gene of the vector $S_w$
$n$ : Number of parameters

**Fig. 1** Modified simple crossover method

< Before Mutation > < After Mutation >

$$S_v^t = [V_1, \dots, V_k, \dots, V_n] \longrightarrow S_v^{t+1} = [V_1, \dots, V_k', V_{k+1} \dots, V_n]$$

Mutation point

where, $V_k'$ : Random value between upper bound and lower bound

**Fig. 2** Uniform mutation method

trings population, selecting two strings randomly in parents population, as shown in Fig. 1. If crossover occurs in $k$-th variable, selecting randomly two strings in $t$-th generation, offstrings of $t+1$-th generation is shown in Fig. 1. In uniform mutation, we selected a random gene $k$ in an individual. If an individual and the $k$-th component of the individual are the selected gene, the resulting individual is as shown in Fig. 2.

Only the $\lambda$ offspring generated by mutation competes for survival and the $\mu$ parents are completely replaced in each generation. Mutation is then performed independently on each vector element by adding a normally distributed Gaussian random variable with mean zero and standard deviation $(\sigma)$, as shown in Eq. (1). After adapting the mutation operator for ES population, if the improved ratio of individual number is fewer than $\delta$, the next generation standard deviation is decreased in proportional to decrease rates of standard deviation $(c_d)$, otherwise, the next generation standard deviation is increased in proportional to increase rates of standard deviation $(c_i)$, as shown in Eq. (2) (Fogel, 1995).

$$V_k^{t+1} = V_k^t + N(0, \sigma^t) \tag{1}$$

$$\sigma^{t+1} = \begin{bmatrix} c_d \times \sigma^t, & \text{if } \phi(t) < \delta \\ c_i \times \sigma^t, & \text{if } \phi(t) > \delta \\ \sigma^t, & \text{if } \phi(t) = \delta \end{bmatrix} \tag{2}$$

where

$N(0, \sigma^t)$ : Vector of independent Gaussian random variable with mean of zero and standard deviation $\sigma$

$V_k^t$ : $k$-th variable at $t$-th generation

$\phi(t)$ : Improved ratio of individual number after adapting mutation operator for population of ES in $t$-th generation

$\delta$ : Constants

***Elitism*** : The best individual in a population is preserved to perform both GA and ES operation in the next generation. This mechanism not only forces GA not to deteriorate temporarily, but also forces ES to use the information to guide subsequent local search in the most promising subspace.

## 3. Aircraft Model

A nonlinear longitudinal dynamic model of a modified F-18 aircraft augmented with thrust vectoring nozzles is used for developing a fuzzy control system for high-angle-of-attack flight. The aerodynamic surfaces are used at normal flight conditions, where the elevators are primary control effectors for longitudinal motion. The thrust vectoring control is useful for high-angle-of-attack flight, low-dynamic-pressure operating conditions. The nonlinearity of both the aerodynamics and the thrust vectoring is preserved in the model. A schematic diagram of the high-angle-of-attack flight loop is illustrated in Fig. 3.

Limiting the motion to the short period longitudinal mode for the high-angle-of-attack flight, the general 6 DOF (degree of freedom) equations representing the flight dynamics of a rigid aircraft are derived by Etkin (1982), which can be reduced to the fifth states model. Figure 4 shows states, force, and moment concerning flight longitudinal motion. The model is described by five state variables; angle-of-attack $(\alpha)$, speed $(V)$, pitch angle $(\theta)$, pitch rate $(q)$, and altitude

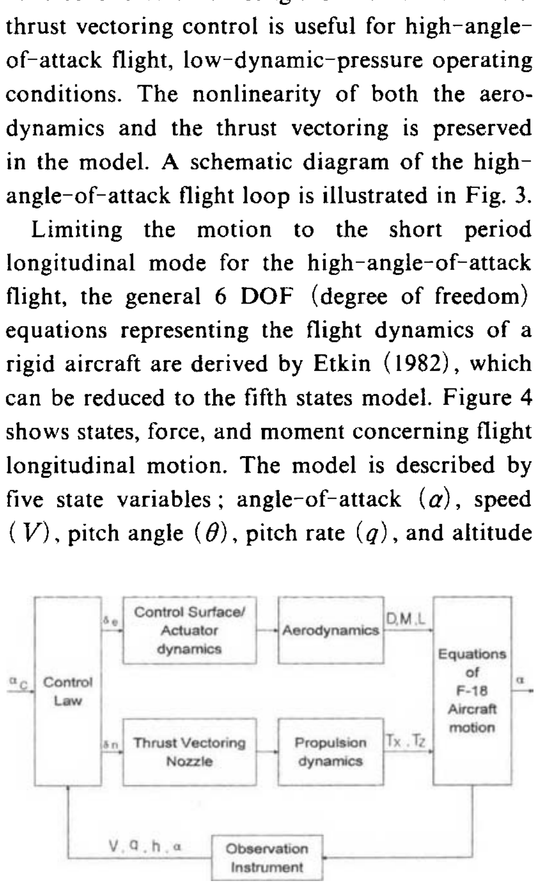



**Fig. 3** Block diagram of flight control system

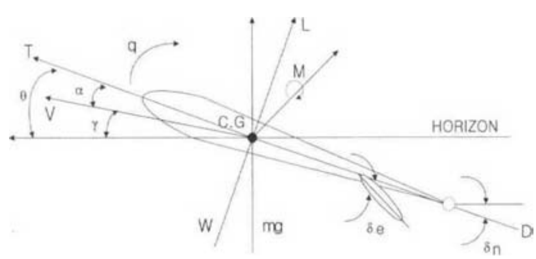



**Fig. 4** Aircraft force and moment diagram

($h$). A nonlinear dynamic model of an F-18 aircraft is described in Egs. (3) ~ (7).

$$m\dot{\alpha}=mq+[mg(\cos\theta\cos\alpha+\sin\theta\cos\alpha) \\ -L-T_x\sin\alpha+T_z\cos\alpha]/V \quad (3)$$

$$m\dot{V}=mg(\cos\theta\sin\alpha-\sin\theta\cos\alpha) \\ -D-T_x\cos\alpha+T_z\sin\alpha \quad (4)$$

$$I_{yy}\dot{q}=M+D(l_x\sin\alpha-l_z\cos\alpha) \\ +L(l_x\cos\alpha+l_z\sin\alpha)+(l_{zt}T_x-l_{xt}T_z) \quad (5)$$

$$\dot{\theta}=q \quad (6)$$

$$\dot{h}=V\sin\gamma=V\sin(\theta-\alpha) \quad (7)$$

where,

$g$ : The gravitational acceleration

$(l_x, l_z)$, $(l_{xt}, l_{zt})$ : The position vector component from the center of gravity to the aerodynamic center and the engine thrust center

$L$, $D$, $M$ : Lift force, drag force and pitching moment

The components of the engine thrust force $T$ are expressed by the thrust vectoring nozzle deflection ($\delta_n$) in the pitch axis:

$$T_x=T\cos\delta_n \quad (8)$$

$$T_z=T\sin\delta_n \quad (9)$$

The drag force ($D$), lift force ($L$), and pitching moment ($M$) are drawn by nonlinear aerodynamic coefficients, so called stability derivatives. The coefficients obtained from wind tunnel data are described by the very complex and nonlinear functions of the angle-of-attack, Mach number and altitude.

The model includes the actuators of elevators which have position limit from −10.5~24 [deg]. The actuators dynamics is modeled as a first-order lag with time constant 1/30 [sec]. It is the same with the case of vane deflection of the thrust vectoring. But the absolute amplitude of nozzle deflection is limited to 20 [deg], and its rate is limited at 80 [deg/sec]. These saturations result in hard nonlinear models of both the thrust vectoring nozzle deflection and the elevator angle ($\delta_e$).

## 4. Design of Fuzzy Logic Controller Using Adaptive Evolutionary Algorithm

Knowledge of experts, and trial and error method have conventionally been used to show FLC's desired control performance, but recently many other approaches using EC are proposed (Won et al., 1999 ; Zhou et al., 2000 ; Juang et al., 2000). Scaling factors such as input/output and the membership function shape of FLC, are are tuned by means of AEA using GA and ES adaptively, as described in chapter 2. Figure 5 shows the architecture for tuning the scaling factors of input/output and the membership function shape of FLC using AEA. As shown in Fig. 5, the input signals to FLC are the angle-of-attack deviation (e) and the change in the angle-of-attack error (de). The output signals of FLC are the elevator angle and the thrust vector nozzle angle. In this paper, the FLC uses the max-min inference and the center of gravity defuzzification.

Figure 6 shows triangular membership function, where linguistic variable NB means "Negative Big", NM means "Negative Medium", NS

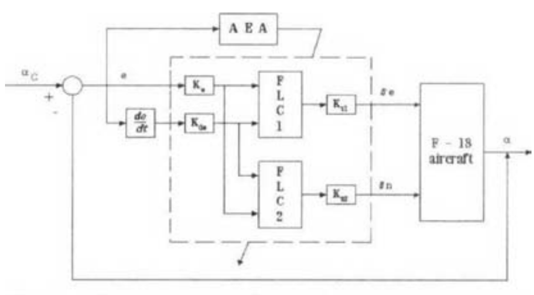



**Fig. 5** Block diagram of fuzzy logic controller using AEA

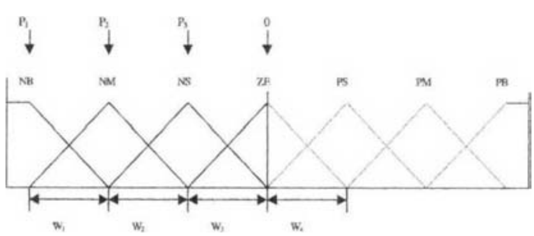



**Fig. 6** Symmetrical membership functions

means "Negative Small" etc. Because we use 7 fuzzy variables (PB, PM, ⋯, NM, NB) respectively, for input/output of FLC, the total membership functions will be 21. Hence, 63 variables that include the center and width of all the membership function will be adjusted. But it takes a long calculation time to 63 variables using AEA, and it suffers from undesirable converging characteristic. In this paper, we fixed the center of ZE to 0, and positive and negative membership functions are constructed symmetrical to the 0. So the number of parameters of FLC will be reduced to 21, which means 3 centers and 4 widths for each variable as shown in Fig. 6.

The flowchart for design of FLC using the proposed AEA is shown in Fig. 7. The procedure of FLC using AEA is as follows :

***Step 1)*** ***Initialize population*** : Strings are randomly generated between the upper bounds and the lower bounds of the membership functions and scaling factors of

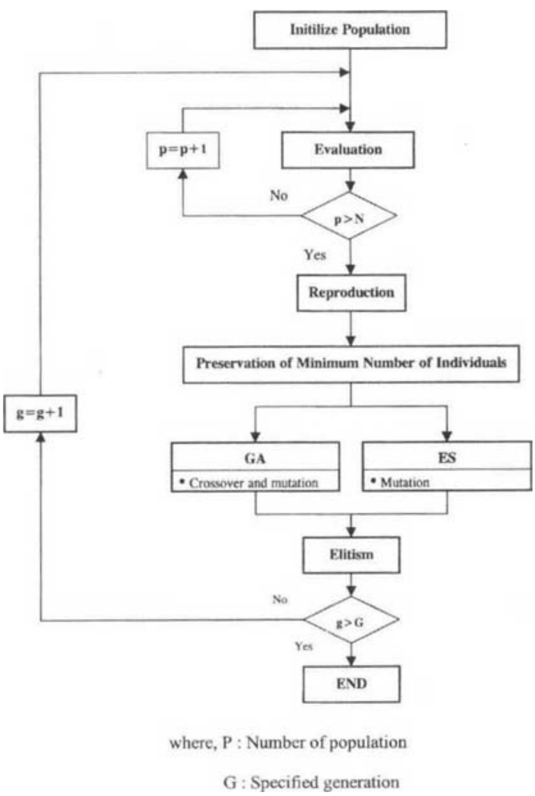
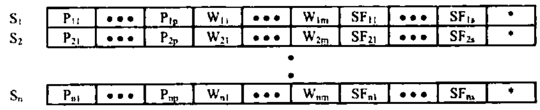



**Fig. 7** Flowchart for the design of FPSS using AEA




where

n : population size
$P_{ij}$ : Center of the membership functions
$W_{ij}$ : Width of the membership functions
$SF_{ij}$ : Scaling factors
$*$ : Operator code

**Fig. 8** String architecture for tuning membership functions and scaling factors

FLC. The operator code is randomly set to decide whether each string is individuals of GA or ES. The configuration of population is shown in Fig. 8. Scaling factors of the FLC are tuned using the AEA.

***Step 2)*** ***Evaluation*** : Each string generated in Step 1) using the fitness function in Eg. (10). As shown in Eg. (10), the absolute deviation between phase angle velocity and phase angle desired is used.

$$Fitness = \frac{1}{100+\sum_{k=1}^{N} | a_k - a_{ref} | + penalty} \tag{10}$$

where

$\alpha_k$ : Phase angle velocity
$\alpha_{ref}$ : Phase angle desired velocity
N : No. of data acquired during T second
*Penalty* : Penalty of pitch rate

***Step 3)*** ***Reproduction*** : Roulette wheel reproduced in proportional to the fitness is used. After reproducing, the individuals operator code of '0' is inserted in the population of GA, and the individuals operator code of '1' is inserted in the population of ES.

***Step 4)*** ***Preservation of Minimum Number of Individuals*** : As both GA and ES become stronger, the minimum number of individuals is guaranteed to prevent offsprings from being eliminated by the GA or ES.

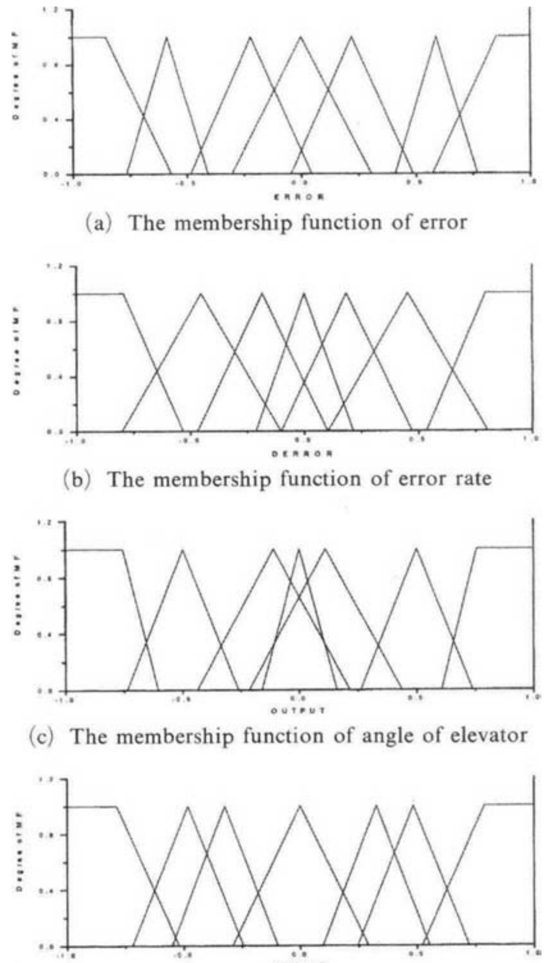
***Step 5)*** ***GA and ES operation***: The individual operator code of '0' accomplishes the crossover and the mutation in GA operators and generates offsprings, and the individual operator code of '1' accomplishes the mutation in ES operator and generates offsprings.

***Step 6)*** ***Elitism*** : Elitism is used for reproducing the best individual of the fitness to GA and ES population by each one.

***Step 7)*** ***Convergence criterion***: Step 2)-Step 6) are iterated until being satisfied to the specified generation.

## 5. Simulation Results

A nonlinear longitudinal model is used to design a high-angle-of-attack flight controller. The proposed FLC is simulated under a nominal flight condition at an altitude of 4,500 m and a speed of around 0.3 Mach. Elevator angle and thrust vectoring nozzle angle are generated from the FLC. Table 1 shows the simulation parameters of AEA for tuning FLC. Figure 9 shows the shape of the membership functions by AEA. Figure 10(a) shows the fitness values by AEA in each generation. Figure 10(b) shows the number of individuals for GA and ES in the AEA. As shown in Fig. 10, the number of individuals of GA is more than that of individuals of ES in early generation. But, from generation to generation, the number of individuals of ES is more than that of individuals of GA. The AEA produces the improved reliability by using the "global" nature of the GA initially as well as the "local" improvement capabilities of the ES from generation to generation.




(a) The membership function of error

(b) The membership function of error rate

(c) The membership function of angle of elevator

(d) The membership function of angle of vector nozzle

**Fig. 9** Tuned membership functions using AEA

**Table 1** Simulation parameters used AEA

| Methods | AEA |
|---|---|
| Size of population | 50 |
| Crossover probability | 0.85 |
| Mutation probability | 0.05 |
| $\delta$ | 0.5 |
| $C_d$ | 0.95 |
| $C_i$ | 1.05 |
| Number of Generation | 200 |

Longitudinal stick step inputs are used to demonstrate the performance of the FLC during nonlinear simulations at a low angle-of-attack of 5 [deg], maximum lift of 40 [deg], high-angle of 60 [deg], pitch rate of 0 [deg/sec], pitch angle of 6.3 [deg] and total speed of 135 [m/sec]. Elevator angle, thrust vectoring nozzle angle, and magnitude of thrust are given by −0.8 [deg], 0 [deg], 1,450 [kgf], respectively. In order to check for the tracking performance of a high-angle-of-attack flight, the proposed FLC is simulated

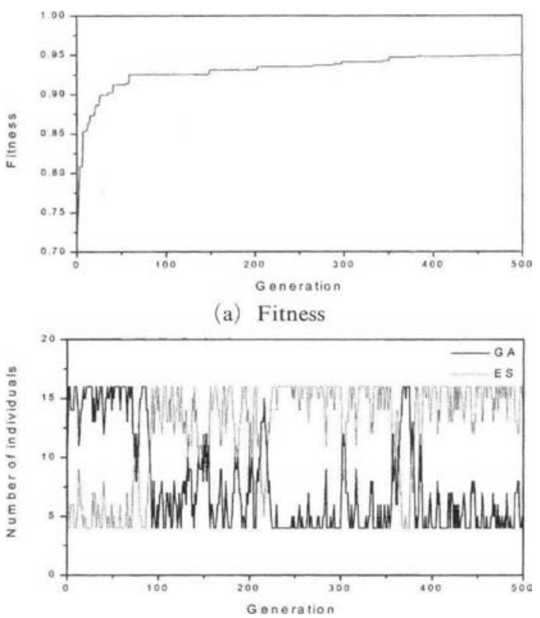



**Fig. 10** Fitness functions and number of individuals of GA and ES

under the flight scenario illustrated in Fig. 11(a) that is considering pitch up, and pitch down command. Therefore, the scenario is devised for the nonlinear simulation of transitional modes with a rapid changing flight command. The resulting angle-of-attack response shows that FLC is to be comparable for the prescribed design goal.

In Table 2, the proposed FLC is compared with the previous control methods (Ostroff, 1992 ; Mohler, 1993) in terms of reaching time and maximum pitch rate. The characteristic of the response are similar to that of the variable gain feedback control method reported by Ostroff (1992). The angle-of-attack of variable gain approach reached 55 [deg] in just under 3.5 [sec] and settling time to 60 [deg] took about 6 [sec]. In prediction adaptive controller, the angle-of-attack reached 55 [deg] in 2.1 [sec] and settling time to 60 [deg] took 3 [sec].

On the other hand, the angle-of-attack of the proposed FLC starts at 5 [deg] trim and reaches 55 [deg] in less 1.2 [sec], then slightly settles the initial command of 60 [deg] in 1.6 [sec]. In Table 2, the proposed FLC comparing with the previous control methods in terms of reaching time and maximum pitch rate. From Tabel 2, the proposed FLC shows better performance than the previous control methods in terms of reaching time though maximum pitch rate is high.

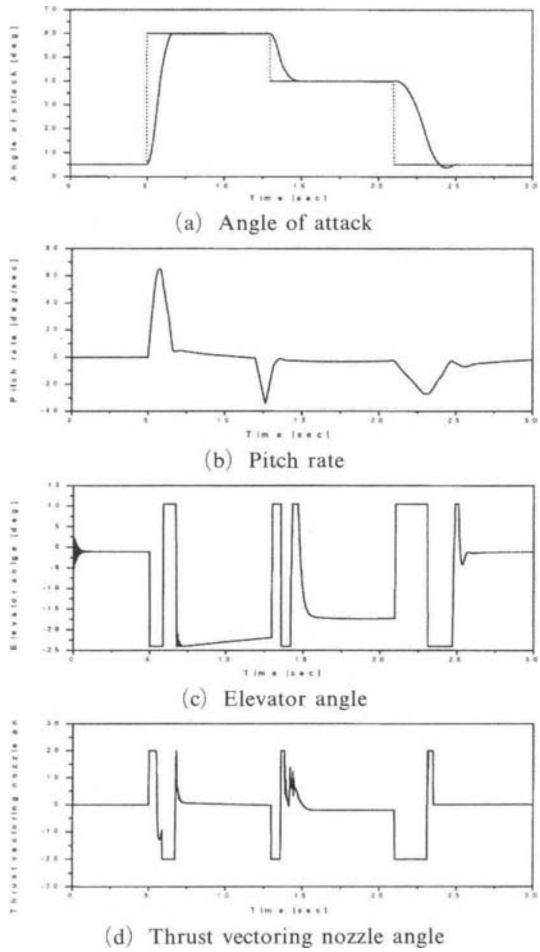
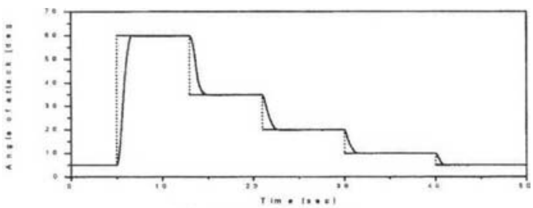


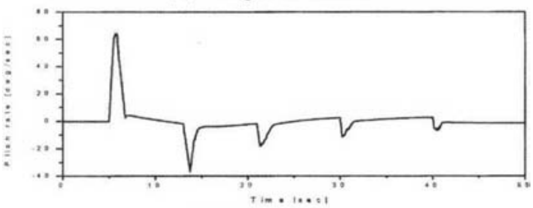

**Fig. 11** Pitch-up and pitch-down maneuver

**Table 2** Performance comparisons of controllers

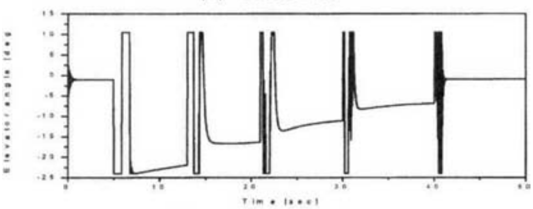
| Methods \ Controllers | Ostroff (1992) | Mohler (1993) | FLC |
|---|---|---|---|
| 55 [deg] reaching time [sec] | 3.5 | 1.8 | 1.3 |
| 60 [deg] reaching time [sec] | 6.0 | - | 1.6 |
| Maximum pitch rate [deg/sec] | 38 | - | 64 |



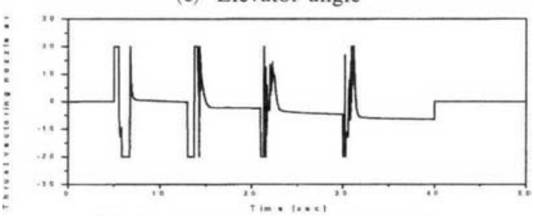
(a) Angle of attack



(b) Pitch rate



(c) Elevator angle



(d) Thrust vectoring nozzle angle

**Fig. 12** New pitch-up and pitch-down maneuver

To show the robustness, the proposed controller is tested under other flight scenario as illustrated in Fig. 12(a). The resulting angle-of-attack response shows that the proposed FLC has a high adaptability for when flight condition is abruptly changed in the wide operating range.

## 6. Conclusions

In this paper, new AEA is applied to search for optimal settings of the membership function's shapes and gains of the inputs and outputs of FLC for a high angle-of-attack flight system for a super-maneuverable version of F-18 aircraft. The AEA is an algorithm that ratio of population to which GA and ES will adapt is adaptively modified in reproduction according to the fitness. By analyzed simulation result of the proposed FLC and conventional methods, the following conclusions are made.

(1) As a result of applying AEA, when designing FLC, in the early generation, it is shown the number of population of GA is more than that of population of ES and the number of population of ES becomes larger as the number of generation increases. This shows that the global search is executed through GA in the early generation and the local search is executed adaptively by means of ES as the number of generation increases.

(2) The proposed FLC shows better control performance than Ostroff's variable gain output feedback control method in terms of settling time and damping effect. To evaluate the robustness of FLC, we tested under other flight scenario. The proposed FLC can provide adaptability for abruptly changing flight condition, in the wide operating range.

## Acknowledgment

This work was supported by Korea Research Foundation Grant(KRF-2002-003-D00113).

## References

Adams, R. J., Buffington, J. M. and Banda, S. S., 1994, "Implementation of a Full-Envolope Controller for a High-Performance Aircraft," *AIAA J. of Guidance, Control, and Dynamics*, Vol. 17, No. 3, pp. 578~580.

Arabas, J., Michalewicz, Z. and Mulawka, J., 1994, "GAVaPS-a Genetic Algorithm with Varying Population Size," *IEEE International Conference on Evolutionary Computation*, pp. 73~78.

Cho, S., 1993, "Nonlinear Adaptive Control Law of Highly Maneuverable High Performance Aircraft," Ph. D. Dissertation, Oregon State University, Dept. of mechanical Engineering

Etkins, B., 1982, Dynamics of flight : Stability and control, John Wiley & Sons.

Fogel, D. B., 1995, "Evolutionary Computation : Towards New Philosophy of Machine Intelligence," *IEEE Press, Piscataway*, NJ, pp. 67~101.

Fogel, D. B., Fogel, L. J. and Atmas, J. W., 1991, "Meta-Evolutionary Programming," *Proceedings 2sth Asilomar Conference on Systems, Signals, and Computers*, pp. 540~545.

Gen, M. and Cheng, R., 1997, Genetic Algorithms & Engineering Design, *A Wiley-Interscience Publication*, pp. 42~67.

Goldberg, D. E., 1989, Genetic Algorithms in Search, Optimization, and Machine Learning, *Addison-Wesley publishing Company*, INC., pp. 1~59.

Gong, D., Yamazaki, G. and Gen, M, 1996, "Evolutionary Program for Optimal Design of Material Distribution System," *IEEE International Conference on Evolutionary Computation*, pp. 139~143.

Juang, C. F., Lin, J. Y. and Lin, C. T., 2000, "Genetic Reinforcement Learning Through Symbiotic Evolution for Fuzzy Controller Design," *IEEE Transactions on Systems Man and Cybernetics, Part B*, Vol. 30, No. 2, pp. 290~302.

Lee, A. W. and Hedrick, J. K., 1994, "Application of Approximation I/O Linearization to Aircraft Flight Control," *ASME J. of Dynamics system Measurement and Control*, Vol. 116, pp. 429~436.

Michalewicz, Z., 1992, Genetic Algorithms+Data Structures=Evolution Programs, *Springer-Verlag*, pp. 119~130.

Mohler, R. R. and Cho, S., Koo, C. S. and Zakrzewski, R. R., 1993, "Nonlinear Stability and Control Study of Highly Maneuverable High Performance Aircraft," *OSU-ECE Report NASA 9201*, Corvallis, OR.

Ostroff, A. J., 1992, "High-Alpha Application of Variable Gain Output Feedback Control," *AIAA J. of Guidance, Control, and Dynamics*, Vol. 15, No. 2, pp. 491~497.

Renders, J. M. and Flasse, S. P., 1996, "Hybrid Methods Using Genetic Algorithms for Global Optimization," *IEEE Transactions on Systems, Man, and Cybernetics-Part B: Cybernetics*, Vol. 26, No. 2.

Schlierkamp-Voosen, D. and Muhlenbein, H., 1996, "Adaptation of Population Sizes by Competing Subpopulations," *IEEE International Conference on Evolutionary Computation*, pp. 330~335.

Schwefel, H. P., 1995, "Evolution and Optimum Seeking," *Sixth Generation Computer Technology Series*, Wiley.

Shi, Y., Eberhart, R. and Chen, Y., 1999, "Implementation of Evolutionary Fuzzy Systems," *IEEE Transactions on Fuzzy Systems*, Vol. 7, No. 2, pp. 109~119.

Spears, W. M., 1995, Evolutionary Programming IV, *The MIT Press*, pp. 73~120.

Srinivas, M. and Patnaik, L. M, 1994, "Adaptive Probabilities of Crossover and Mutation in Genetic Algorithms," *IEEE Transactions on Systems, Man and Cybernetics*, Vol. 24, No. 4, pp. 656~667.

Won, T. H., Song, D. S. and Lee, M. H., 1999, "A Design of Fuzzy Variable Structure Controller for F-18 Aircraft," *KSME*, Vol. 23, No. 12, pp. 2109~2119.

Zhou, Y. S. and Lai, L. Y., 2000, "Optimal Design for Fuzzy Controllers by Genetic Algorithms," *IEEE Transactions on Industry Applications*, Vol. 36, pp. 93~97.