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RESEARCH ARTICLE

PRELIMINARY DESIGN OF ONBOARD GUIDANCE SYSTEM USING DYNAMICALLY DISTRIBUTED GENETIC ALGORITHM FOR EXPERIMENTAL WINGED ROCKET.

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Abstract

The authors have been developing the guidance system of winged rocket using dynamically distributed genetic algorithm (DynDGA) for trajectory optimization. DynDGA is an advanced genetic algorithm (GA) which can enhance the variety of trajectories and maintain the trajectory search performance. However, DynDGA requires higher computing power. One of the simple solution for this problem is to reduce the number of individuals and generations, but it also degrades the solution search capability. For the implementation, authors need to make a tradeoff between these problems. Evolutionary algorithms (EAs) have proven successful in a vast number of static applications and the number of papers produced in this area is growing rapidly. However, they also seem to be particularly suitable for dynamic and stochastic optimization problems such as natural selection. The authors performed some simulations, and the results succeeded to reach the target point. However, at some initial conditions, the simulation could not reach near the target point. This paper describes the simulation results of DynDGA onboard guidance system for experimental winged rocket in dynamic environment.

Introduction:-

The Reusable Launch Vehicle (RLV) aimed at the low-cost space transportation system is an idea, which has been planned for more than half a century. However, RLVs have not been realized except the U.S. space shuttle, which has accomplished partial reuse. Kyushu Institute of Technology has been developing winged fully reusable space transportation system (as in Figure 1) and studying autonomous guidance/control algorithm, composite fuel tank and aerodynamic design problems of RLVs [1]. Real-time guidance is one of the challenging tasks because the system needs to generate an optimized guided trajectory even under abort flight. The objective of this study is to develop an algorithm to generate optimal trajectory without any pre-determined trajectory under any uncertainties.

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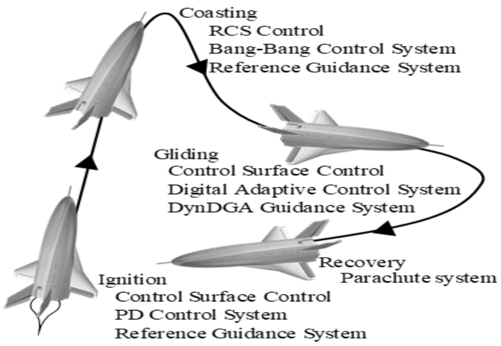

Figure 1:- Reusable space transportation system.

The authors have been developing the guidance system using dynamically distributed genetic algorithm (DynDGA [2)]) for trajectory optimization. DynDGA is an advanced genetic algorithm (GA) which can enhance the variety of trajectories and maintain the trajectory search performance. The advantage of adapting DynDGA is obtaining non-divergent solutions, compared with conventional studies such as SQP methods [3)] and numerical methods. From the past studies, the basic algorithm for guidance using DynDGA has been developed. As a next step, the authors have been developing the guidance system for real time implementation. This paper describes the simulation results of DynDGA onboard guidance system for experimental winged rocket in dynamic environment.

Dynamically Distributed Genetic Algorithm:-

GA is a search heuristic algorithm that imitates the process of natural selection. Figure 2 shows the flowchart of GA. At first, GA creates an initial individual group and calculates their fitness. Fitness is the measure of how well the individual is fitted to the conditions. Next, the GA selects two individuals and their crossover is performed. Finally, GA calculates the individuals' fitness which are generated by the crossover, and selects the individuals that survive to the next generation. Mutation is a process to change the gene values at random with a rate. It makes to escape from the local solution. This procedure is repeated many times, and the optimal result is obtained.

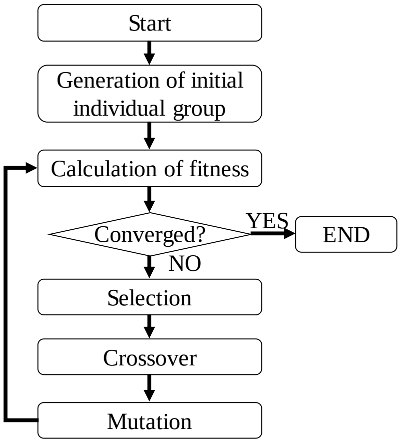

Figure2:-Flowchart of GA

An important feature of this search methodology is the diversity of individuals. In a normal search for an optimal solution, searching is fallen into a local solution. In this situation, escape from the local solution may be achieved by using mutation or the distributed genetic algorithm (DGA [4)]). Figure 3 shows the schematic illustration of the DGA model. Using DGA, Individuals are divided into sets of populations called islands, the search of an optimal solution is conducted in each island independently. For every generation, the DGA trades individuals between islands, which is called migration. This process makes it possible to maintain the variation of individuals and to enhance the search performance.

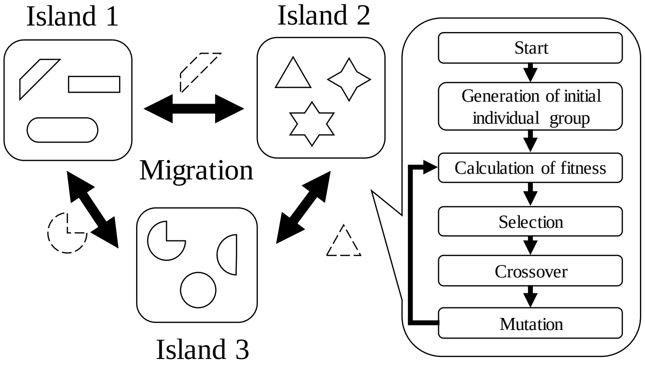

Figure 3:- Schematic illustration of DGA.

DynDGA is an extension to DGA. Figure 3 shows the model of DynDGA. In DynDGA, the population is distributed into islands based on their dissimilarity, and the number of islands changes dynamically as the optimization proceeds. Hierarchic clustering method [5)] is employed to distribute the population into islands. The calculation of the dissimilarity is done using the combinatorial method. Among several approaches, the Ward's method [6)] is used in this simulation. As a result of dynamic clustering, some similar islands are merged, and an island is divided into several islands if necessary. By repeating these procedures, some optimized flight trajectories are finally obtained in each island.

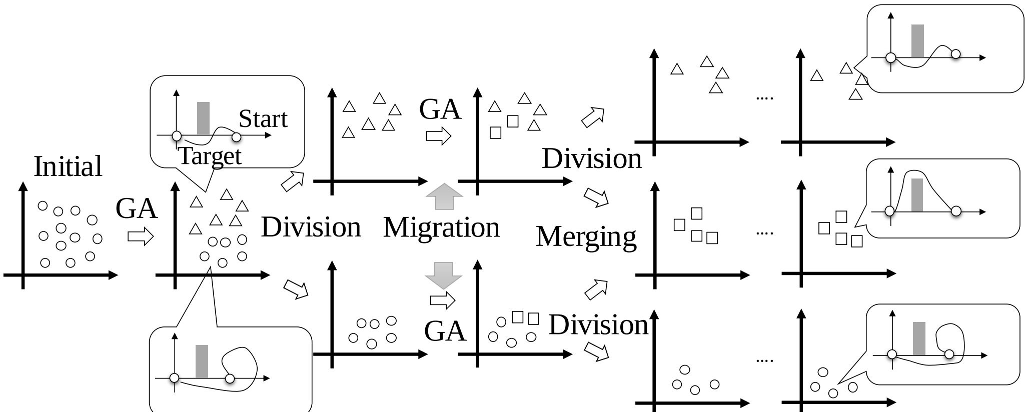

Figure 3:- Schematic illustration of DynDGA.

Onboard Guidance System:-

Winged rocket model

Kyushu Institute of Technology has been developing reusable space transportation system called WIRES (Winged REusable Sounding rocket, as in Figure 4) since 2005. The objective of this vehicle is to reach 100km altitude and realize the sub-orbital space travel. In the return phase, this rocket glides to a target point using a fully autonomous guidance system based on DynDGA trajectory optimization.

In this simulation, the rocket model is a subscale experimental winged rocket called "WIRES#015". The mission objective of this vehicle is to evaluate the real-time optimal trajectory generation using DynDGA, demonstrate the LOX-Methane propulsion system, reentry attitude control system by gas jet thrusters and recovery by two-stage parachute and airbags. Table 1 shows the specification of WIRES#015

Figure 4:- WIRES#015

Table 1:- WIRES#015 specifications

Length	[m]	4.6
Launch mass	[kg]	1000
Wing area	[m^2]	2.68

DynDGA condition

Table 2shows the DynDGA condition. Terminating generation depends on simulation types.

Table 2:- DynDGA condition

Number of individuals	200
Number of gene	24
Number of characteristics	40
Clustering border	4×10^8
Differential equation solution	4thRunge-Kutta
Crossover method	0.5-Blend crossover
Selection method	Elitist recombination
Mutation	0.1
Migration step	10
Differential equation step	0.5

Fitness

The objective functionsare defined as written in eqs. (1)-(6).

$$F = \frac{1000}{x_{\mathrm{e}} + x_{\mathrm{err}} + \psi_{\mathrm{err}} + x_{\mathrm{obs}}} \tag{1}$$

$$x_{\mathrm{e}} = \frac{x_{\mathrm{flight}}}{x_{\mathrm{base}}} \tag{2}$$

$$x_{\mathrm{err}} = 10\,\frac{|\xi_{\mathrm{f}} - \xi_{\mathrm{t}}| + |\eta_{\mathrm{f}} - \eta_{\mathrm{t}}| + |h_{\mathrm{f}} - h_{\mathrm{t}}|}{x_{\mathrm{base}}} \tag{3}$$

$$\psi_{\mathrm{err}} = \frac{50|\psi_{\mathrm{f}} - \psi_{\mathrm{t}}|}{\pi} \tag{4}$$

$$x_{\mathrm{obs}} = 0 \tag{5}$$

$$x_{\mathrm{base}} = |\xi_{\mathrm{t}} - \xi_{\mathrm{i}}| + |\eta_{\mathrm{t}} - \eta_{\mathrm{i}}| + |h_{\mathrm{t}} - h_{\mathrm{i}}| \tag{6}$$

where x_{flight} is trajectory length. In short, the objective function is the minimization of the summation of flight time, the difference between the target point and final point in terms of down-range, cross-range, altitude, azimuth, and the flight duration when the obstacle area is violated. However, the obstacle parameter is set to zero because the simulation doesn't have obstacle area.

For calculating the fitness, the guidance system solves the differential equation of motion as in eqs. (7)-(19).

$$m\frac{dV}{dt} = -\frac{1}{2}\rho V^2 S_w C_D - mg\sin\gamma \qquad (7)$$

$$mV\frac{d\gamma}{dt} = \frac{1}{2}\rho V^2 S_w C_L \cos\phi - mg\cos\gamma \qquad (8)$$

$$mV\cos\gamma\frac{d\psi}{dt} = \frac{1}{2}\rho V^2 S_w C_L \sin\phi \qquad (9)$$

$$\frac{dh}{dt} = V\sin\gamma \qquad (10)$$

$$\frac{d\xi}{dt} = V\cos\gamma\cos\psi \qquad (11)$$

$$\frac{d\eta}{dt} = V\cos\gamma\cos\psi \qquad (12)$$

$$C_L = 3.232\alpha - 0.0574 \qquad (13)$$

$$C_D = 3.146\alpha^2 - 0.1715\alpha + 0.0805 \qquad (14)$$

$$d_\alpha(t) = ea_{0\alpha} + (1 - e\,|\,a_{0\alpha}\,|)\sum_{n=1}^{3}\left\{\frac{a_{n\alpha}\cos(n\omega_\alpha t) + b_{n\alpha}\sin(n\omega t)}{3\sqrt{2}}\right\} \qquad (15)$$

$$\alpha(t) = d_\alpha(t) \times \mathrm{limit}_\alpha \qquad (16)$$

$$d_\phi(t) = ea_{0\phi} + (1 - e\,|\,a_{0\phi}\,|)\sum_{n=1}^{3}\left\{\frac{a_{n\phi}\cos(n\omega_\phi t) + b_{n\phi}\sin(n\omega t)}{3\sqrt{2}}\right\} \qquad (17)$$

$$\phi(t) = d_\phi(t) \times \mathrm{limit}_\phi \qquad (18)$$

$$\begin{cases} 10 \le \alpha \le 20 \\ -60 \le \phi \le 60 \end{cases} \qquad (19)$$

where a_0, a_n, b_n and ω are optimized variables, e is the user defined parameter and t is time.

Other simulation condition

Figure 5shows a flight area image. Table 3 shows the initial conditions of the first trajectory. Table 4shows the target conditions.

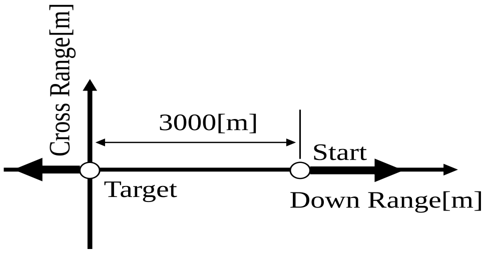

Figure5:- Flight area

Table 3:- Initial condition

Velocity	[m/s]	100
Flight path angle	[°]	0
Azimuth	[°]	0
Down range	[m]	3000
Cross range	[m]	0
Altitude	[m]	5000

Table 4:- Target condition

Down range	[m]	0
Cross range	[m]	0
Altitude	[m]	1000
Azimuth	[°]	180

Figure 6shows the outline of simulation flow. In this paper, there are 4 simulation patterns. First simulation pattern is single shot guidance. In this pattern, the guidance system generates an optimal trajectory for every 5 seconds. However, there are no inheriting data to use in the next optimization. Second pattern is continuous optimization. In this pattern, the guidance system continuously generates an optimal trajectory during the simulation, and it updates the optimal solution for every 100 generations. Third pattern is same as second pattern. In this pattern the guidance system updates the optimal solution for every 800 generations. Final pattern is also similar to second pattern. In this pattern the guidance system updates the optimal solution for every 10 generations.

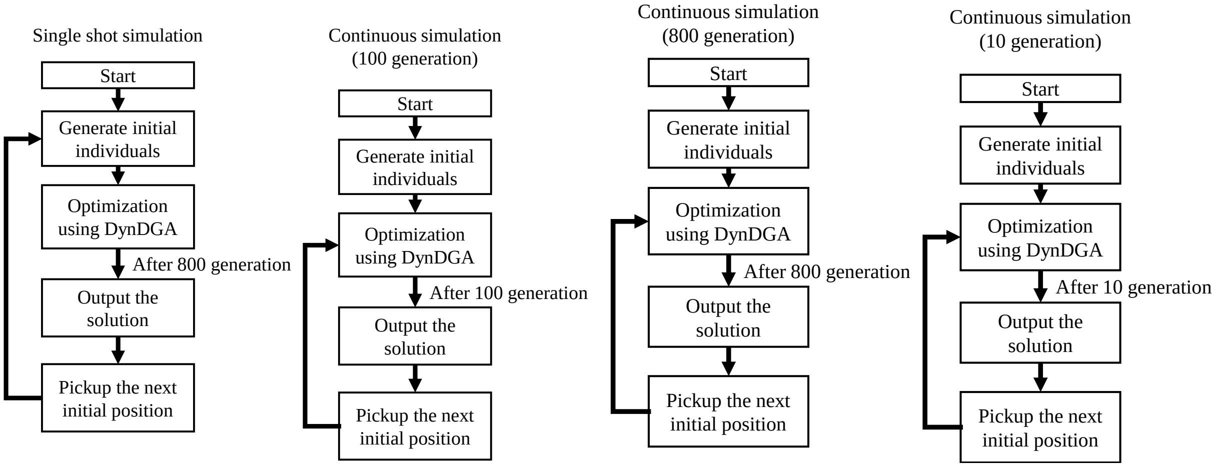
Single shot simulation
Start
Generate initial individuals
Optimization using DynDGA
After 800 generation
Output the solution
Pickup the next initial position
Continuous simulation (100 generation)
Start
Generate initial individuals
Optimization using DynDGA
After 100 generation
Output the solution
Pickup the next initial position
Continuous simulation (800 generation)
Start
Generate initial individuals
Optimization using DynDGA
After 800 generation
Output the solution
Pickup the next initial position
Continuous simulation (10 generation)
Start
Generate initial individuals
Optimization using DynDGA
After 10 generation
Output the solution
Pickup the next initial position

Figure 6:- Simulation pattern

Simulation Result:-

Each simulation patterns were able to reach near the target position. Table 5 shows the outline of the simulation results. As the interval between the output solutionsdecreased, the total simulation time also decreasedin the continuous simulation. However, the error of azimuth increases. From the fitness profile, continuous simulation has better fitness than single shot simulation.

In the real time implementation, the guidance system needs to set the interval not for the off springgeneration but for calculation time. This is because the calculation time depends on the initial conditions. As a result, the interval time is based on the calculation time which is calculating the 100 generations.

Table 5:- Outline of simulation result

	Calculation time	Error of distance	Error of azimuth
	[s]	[m]	[°]
Single shot	5167	0.18	6.42
Interval of 100 generation	1082	0.23	39.6
Interval of 800 generation	7897	0.01	16.9
Interval of 10 generation	243	104	76.3

Single shot generation

The simulation result is shown in Figure 7. This showsall the optimal trajectories produced. The symbol “*” is the initial position at which the trajectory is generated. Each trajectory could reach near the target point. Figure 8 shows the fitness value profile. Each fitness starts with a low value.

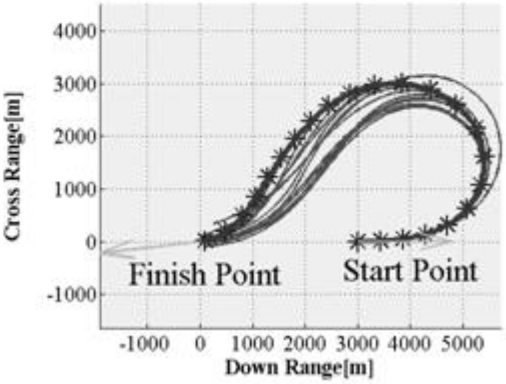

Figure 7:- Trajectory of single shot simulation

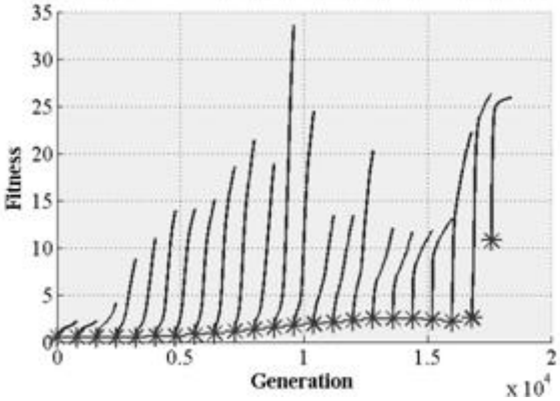

Figure 8:- Fitness profile of single shot simulation

Interval of 800 generation

The simulation result is shown in Figure 9. This shows all the optimal trajectories produced. The symbol "*" is the initial position at which the trajectory is generated. Each trajectory could reach near the target point,however the final trajectory's azimuth has larger error. Figure 10 shows the fitness value profile. Each fitness value starts with a higher fitness value than single shot pattern, however each fitness value terminates with a lower fitness value than single shot pattern.

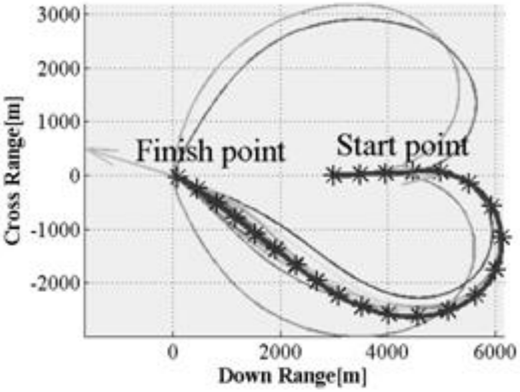

Figure 9:- Trajectory of continuous generation (Interval of 800 generation)

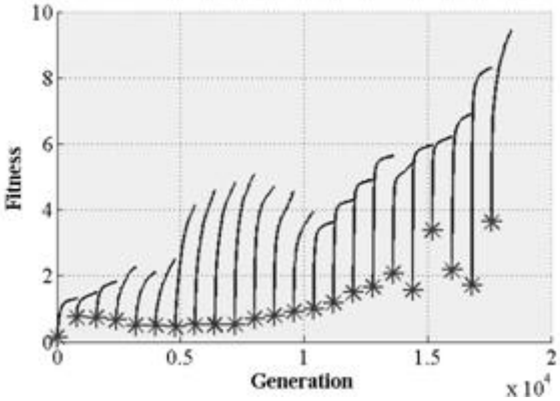

Figure10:- Fitness profile of continuous generation (Interval of 800 generation)

Interval of 100 generations

The simulation result is shown in Figure 11. This shows all the optimal trajectories produced. The symbol "*" is the initial position at which the trajectory is generated. Each trajectory could reach near the target point. However, the final trajectory's azimuth has larger error. Figure 12 shows the fitness value profile. Each fitness value starts with a higher fitness value than single shot pattern. The final fitness value is less than the single shot pattern.

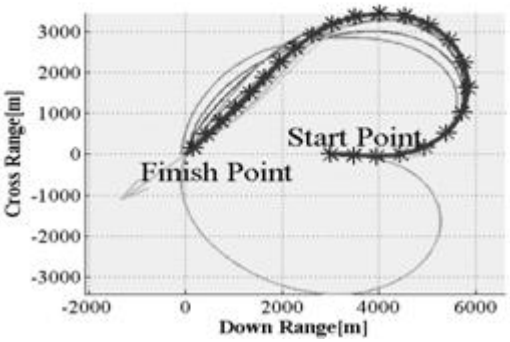

Figure11:- Trajectory of continuous generation (Interval of 100 generation)

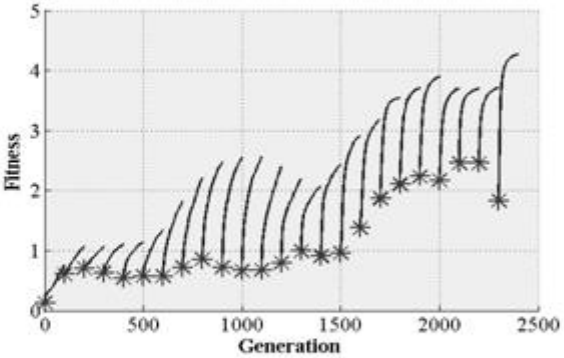

Figure12:- Fitness profile of continuous generation (Interval of 100 generation)

Interval of 10 generations

The simulation result is shown in Figure 13. This shows all the optimal trajectories produced. The symbol "*" is the initial position at which the trajectory is generated. Earlier trajectory could not reach near the target point. However, final trajectory could reach near the target. Figure 14 shows the fitness value profile. Each fitness value starts with a higher value than single shot pattern. The final fitness value is less than the single shot pattern.

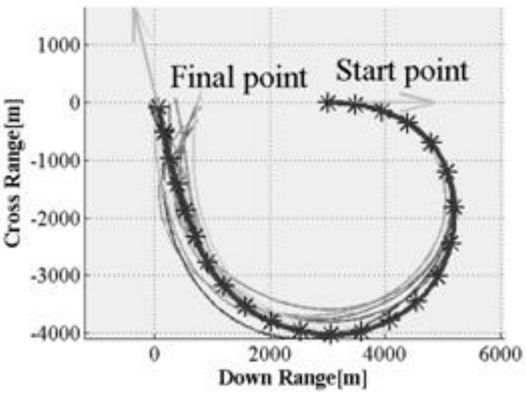

Figure13:- Trajectory of continuous generation (Interval of 10 generation)

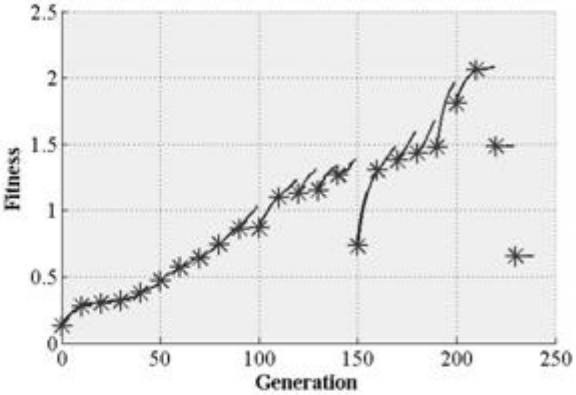

Figure14:- Fitness profile of continuous generation (Interval of 10 generation)

Conclusion:-

This paper describes the simulation results of DynDGA onboard guidance system for experimental winged rocket in dynamic environment. From the results, the continuous generation type which has the interval set at 100 generation appears to be optimal than the other generation types. In future, authors continue the simulation for real time implementation and validate on the experimental winged rocket.

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