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Parameter optimisation of Genetic Algorithm Utilising Taguchi Design for Gliding Trajectory Optimisation of Missile

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ABSTRACT

The present study aims to establish a Genetic Algorithm (GA) methodology to optimise the missile gliding trajectory. The trajectory optimisation was carried out by discretising the angle of attack (AOA), subsequent transformation of the optimal control problem to a nonlinear programming problem (NLP), and resolving the optimal control problem to attain a maximised gliding range. GA is employed for resolving optimal control problem. Taguchi design of experiments was proposed contrary to the full factorial method to ascertain the GA parameters. The experiments were designed as per Taguchi's L_{27} orthogonal array. The systematic reasoning ability of the Taguchi method is exploited to obtain better selection, crossover, and mutation operations, and consequently, enhance GA performance. An analysis of variance (ANOVA) is performed to evaluate the influencing factors in the results. Crossover function and population size are observed as impacting parameters in trajectory optimisation, accompanied by selection, crossover fraction, mutation rate, and number of generations. An Artificial Neural Network (ANN) approach was enforced to anticipate the significance of GA parameters. Based on Taguchi design of experiments, analysis of variance, and artificial neural network methods the optimal parameters of GA were selected. It is observed that the maximum gliding distance is achieved after GA parameter tuning. It is noticed from the simulation results that the missile gliding range is enhanced in comparison to earlier ones. The simulation results also show the efficiency of the proposed procedure through different test cases.

Keywords: Missile gliding trajectory optimisation; Genetic algorithm; Taguchi method; Analysis of variance; Artificial neural network

1. INTRODUCTION

Optimisation of a missile trajectory is a challenging task and plays a pivotal role in the area of defense. The missile's range could be enhanced while it travels through the optimised trajectory. Several factors were considered while performing trajectory optimisation. The factors involved are total flight time, AOA, path angle, velocity, and altitude. Defined constraints and boundary conditions must be satisfied. Optimisation of trajectory gets complicated owing to the preceding aspects. As a consequence, the difficulty of finding the optimal solution increases, and tougher for traditional methods to resolve the problem[1-3].

Researchers have proposed various methodologies to resolve trajectory optimisation challenges, which are classified as direct and indirect methods[3-12]. Though an accurate solution could be achieved using indirect methods by rigorous derivation; it is perceptive to primary guesses of castrates[13-14]. Therefore, the approach cannot be employed in troublesome situations. In contrast, direct methods find solutions by parameterisation and discretion while transforming conventional optimal control problems into parameter optimisation problems. As a result, the complexity of programming is reduced, which accomplishes the direct method widely used. The direct method is beneficial to obtain an approximate optimal solution with a higher probability[15-16].

Trajectory optimisation of aerospace vehicles using evolutionary algorithms is a current state-of-the-art research problem. GA is one of the well-known evolutionary algorithms that have gained increasing importance in recent years[17-24]. This could be attributed to the capability of solving both discrete and continuous optimisation problems, the independence of functional derivatives, and avoidance of getting caught in local optima[25]. Moreover, GA is well exercised in flight trajectory optimisation[26-41]. Suzuki[26], *et al.* addressed the reentry trajectory design problem using GA, whereas a hybrid GA with collation method is employed to solve the Earth-Mars orbit transfer problem[27]. The Trajectory optimisation problem of a spacecraft is addressed by employing multiple shooting-based NSGA-III [28]. Li[29], *et al.* demonstrated that the climb flight path optimisation problem of aircraft could be effectively solved by quantum GA. Kumar[30], *et al.* adopted GA and optimised hypersonic boost-glide vehicle trajectory. Sun[31],

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et al. implemented GA based method in solving the trajectory optimisation problem. GuoQuiang[32], *et al.* surveyed various algorithms for flight trajectory optimisation.

Yokoyama[33], *et al.* employed GA combined with the gradient method in solving the optimisation problem of a flight trajectory. A flight trajectory was optimised using GA for combined vertical and lateral navigation[34]. Visser[35], *et al.* proposed a method to configure trajectories for averting unattainable in the optimisation of environmental trajectory. GA has also been employed for the trajectory optimisation of a rocket.[36] Seddaoui[37], *et al.* reported a novel optimised space robot trajectory by employing GA. Liu[38], *et al.* presented a GA-based methodology for trajectory optimisation of digital twin robots. Dancila[39], *et al.* proposed new flight trajectory optimisation methods for cost minimisation relying on GA. A multi-objective trajectory optimisation technique relied on GA was reported by Wang[40], *et al.* for achieving an efficient and stable solution for the robot manipulators task. Rahman[41], *et al.* optimised an energy-efficient path using GA for unmanned aerial vehicles (UAVs) - Internet of Things (IoT) collaborative system. Based on the literature survey; GA has been selected for the current study.

At times, optimal results are scanty owing to the selection of improper algorithm parameters. The selection of optimal parameters is beneficial for achieving results with less randomness. Moreover, the algorithm parameters could be suitably utilised to enhance search efficiency. However, it is difficult to identify suitable parameters for a given problem[42]. Yuan-bin[43], *et al.* studied the influence of optimal parameter selection on the optimisation behavior of the firefly algorithm relying on a few benchmark functions. Ant colony optimisation algorithm parameters were optimised by Ramli[44], *et al.* for better performance in T-way IOR testing.

Xue[45], *et al.* optimised the parameters of the bat algorithm utilising an orthogonal array design. Yang[46], *et al.* reviewed intelligent algorithms with their crucial parameters and analysed parameter optimisation techniques. Huang[47], *et al.* surveyed the automatic tuning techniques of intelligent algorithm parameters for performance optimisation. The optimisation performance of GA could be enhanced by setting appropriate parameters like population size, number of generations, selection, crossover function, crossover fraction, mutation rate, and so on[48]. It is found in the literature that the Taguchi method helped to decrease the interference generated by randomness and ascertain GA parameters[49-51]. The advantage of the Taguchi method is proper parameter selection in GA without performing complete parameter experiments due to the orthogonal array table. Additionally, it helps to reduce the number of iterations and achieve an optimal solution with less randomness[48]. ANOVA analysis is a broadly used statistical approach that finds the contribution of individual algorithm parameters toward problem optimisation and confirms the reliability of the Taguchi method. Moreover, ANN possesses the capability to learn the complex and non-linear relationship between input and output data. ANN could be able to anticipate hidden data and deduce hidden relationships. Therefore, a methodology relying on Taguchi design of experiments, ANOVA, and ANN was proposed to select suitable GA parameters for optimisation of glide phase missile trajectory.

Present research conveys a missile gliding trajectory optimisation problem. Initially, the angle of attack (AOA) is discretised, the optimal control problem is transformed into a nonlinear programming problem (NLP), and eventually, the problem is resolved to attain maximum gliding range. This paper also proposes the optimal parameter setting of GA relying on the Taguchi design of experiments, ANOVA, and ANN approach. The salient contribution of the present study includes performance enhancement of GA by setting appropriate parameters like population size, number of generations, selection, crossover function, crossover fraction, and mutation rate. It is better than a random selection of GA parameters. Moreover, it helps in reducing disturbance caused by randomness, reducing the number of iterations, and achieving an optimal solution with less randomness. Based on the above studies, the GA parameters were determined and employed to optimise the missile's gliding trajectory. The remainder of the present article is organised as follows: Section 2 describes the trajectory optimisation characteristics analysis, and Section 3 represents experimental results and discussion. Conclusions are drawn in Section 4.

2. TRAJECTORY OPTIMISATION CHARACTERISTICS ANALYSIS

The effects of aerodynamics and the earth's gravitational force are considered during the gliding stage of a missile. However, the effect of the earth's curvature and rotation is ignored. This could be due to the modest range addressed in the current study[52]. The schematic figure with the free body diagram is presented in Fig. 1, and the equations of motion in the missile gliding stage are presented below[53-54].

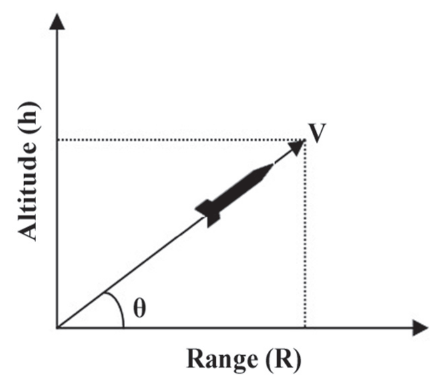

Figure 1. Schematic figure with the free body diagram.

$$\left.\begin{aligned} m_0 \frac{dV}{dt} &= -C_D qs - m_0 g \sin\theta \\ m_0 V \frac{d\theta}{dt} &= C_L qs - m_0 g \cos\theta \\ \frac{dR}{dt} &= V\cos\theta \\ \frac{dh}{dt} &= V\sin\theta \end{aligned}\right\} \quad (1)$$

where, m_o-missile mass; g-gravitational acceleration; q-dynamic pressure; V-velocity; θ-path angle; s-reference area; h-altitude;

R-gliding range; C_L- coefficient of lift and C_D- coefficient of drag

The objective of current research is to maximize the missile glide range while fulfilling constraints and boundaries. The missile trajectory was optimised, acknowledging all the control response and aerodynamics off-nominal situations. Therefore, it is essential to maintain AOA and altitude within the maximum allowable limits for better control. The missile's glide trajectory is optimised under conditions of free end and free time. The C_D and C_L follow the aerodynamics fitment formulae and are realised via linear interpolation regarding AOA (α), altitude (h), and Mach number (*Ma*) as follows: [52]

$$C_D = f_D(h, Ma, \alpha) \tag{2}$$

$$C_L = f_L(h, Ma, \alpha) \tag{3}$$

where, f_D is the linear interpolation function for drag and f_L is the linear interpolation function for Lift.

2.1 Constraints and Boundary Conditions

The missile structure and control system constrain it during flight. The terminal constraints must be considered during trajectory optimisation. The purpose of optimisation is gliding range (*R*) maximisation of missile.

$$\text{Max } F = R(\tau_f) \tag{4}$$

$$-10^o \leq \alpha \leq 10^o \tag{5}$$

$$h(\tau_f) = h_f \tag{6}$$

where, τ_f is terminal time and h_f is the altitude at the terminal time (τ_f)

Due to the convergence property of GA, an optimal solution could be achieved with a defined possibility. A tolerance limit is introduced for altitude (h) of missile.

$$h_f - \Delta h \leq h(\tau_f) \leq h_f + \Delta h \tag{7}$$

When aircraft terminal altitude $h(\tau_f) = 0$, the limit of tolerance Δh =100 m.

2.2 Design Variables Selection

During missile flight aerodynamic control is a crucial factor that is mainly affected by AOA[55-57]. The missile range could be improved by designing AOA (Eqn. 2-3). It should not be too high or too low, which causes large aerodynamic drag and miss distance at the predicted impact point, respectively.[1] The rate at which AOA change should be stable, bounded and simple to realise in practical engineering requirements. The flight time is free in the gliding stage and needs to be optimised. Hence, τ_f and α are the control variables.

The time variable (τ_0 to τ_f) is divided in N equal subintervals such as $\tau_0<\tau_1<\tau_2<...........<\tau_{N-2}<\tau_{N-1}<\tau_N=\tau_f$.

In every subinterval $\tau \in \tau_i, \tau_{i+1}$., (i = 0, 1,.., N-1), spline interpolation is utilised for anticipating the AOA $\alpha(\tau)$.

$\alpha(\tau) = interp1(\tau_i, \tau_{i+1}., \alpha_i, \alpha_{i+1}., \tau, \text{'}spline\text{'})$

where, α_i and α_{i+1} are the AOA values at τ_i and τ_{i+1}, respectively.

AOA should be restored by N+1 unknown parameters $\alpha_0, \alpha_1, \alpha_2,..,\alpha_{N-2}, \alpha_{N-1}, \alpha_N$ by 1D spline interpolation. Additionally, as terminal time (τ_f) is free, the parameter vector $p = (\alpha_0, \alpha_1, \alpha_2,..,\alpha_{N-2}, \alpha_{N-1}, \alpha_N, t_f)$ is taken as design variable.

The motion equations were simulated using MATLAB R2016a and HP computer model-Z6G4. The Indian Standard Atmosphere (IS196) is used in the course of simulation. The control variable is $p = (\alpha_0, \alpha_1, \alpha_2,..,\alpha_{N-2}, \alpha_{N-1}, \alpha_N, t_f)$. Real-coded GA is employed for optimising the objective function to achieve optimal result.

2.3 Genetic Algorithm

Genetic algorithm is a widely used approach that imitates the basic idea of biological evolution. The main GA parameters are population size, number of generations, selection, crossover function, crossover fraction, and mutation rate. GA is advantageous when compared to traditional optimisation algorithms in terms of its ability to deal with complex problems and its parallelism, i.e., being easily adaptable and modifiable for different problems. Crossover and mutation operators make the population diverse and thus possess high immunity against trapping in local optima. The offspring generated act like independent agents, thereby exploring search space in multiple directions simultaneously. It is a good choice for multi-objective and wide-ranging optimisation problems.[58-60]

2.4 Application of GA

The control variable $p = (\alpha_0, \alpha_1, \alpha_2,...,\alpha_{N-2}, \alpha_{N-1}, \alpha_N, t_f)$ needs to be optimised. The population is comprised of *m* chromosomes selected at random for exploring in the *N+2* dimensional search space of each chromosome. $p_i = (\alpha_{i0}, \alpha_{i1}, \alpha_{i2},...,\alpha_{iN-2}, \alpha_{iN-1}, \alpha_{iN}, t_{if})$ is the ith chromosomes, $i = 1, 2, 3,\ldots m$.

3. RESULTS AND DISCUSSION

3.1 Taguchi Design of Experiments and Analysis of Variance (ANOVA)

Taguchi method is frequently exploited in statistical analysis, and an orthogonal array is a good approach to work with a huge number of parameters[49]. The Taguchi method helps in analysing various parameters without conducting a huge number of experiments. It helps in finding key parameters that have a significant effect on performance characteristics, while parameters with a negligible effect could be ignored. This technique ensures that all levels of each factor are equally investigated[61-62].

Random selection of GA parameters results in diverse optimal results, and solutions may still vary with the same parameter setting. The selection of optimal GA parameters and achieving optimal results with less randomness using the Taguchi method is the main objective. The steps involved in Taguchi design of experiments are as follows:

Step 1: Setting the fitness function as per Eqn. (1).

Step 2: Identifying control factors for GA as shown in Table 1.

Step 3: The L_{27} orthogonal Table 2 in the Taguchi design of experiments is selected relying on control factors and their level to envisage the optimum GA parameter tuning.

Step 4: To take account of disturbance characteristics, every parameter group of the L_{27} orthogonal array (Table 2) for individual experiment runs five times and results are recorded as f_i, i = 1, 2,.., 5. The signal-to-noise ratio (*S/N*) 'Larger-the-Better (LTB)'

Table 1. Genetic algorithm parameter level setting

Parameter	Level		
	1	2	3
A (population size)	100	150	200
B (number of generations)	100	150	200
C (selection)	Roulette Wheel	Tournament	Rank
D (crossover fraction)	0.6	0.7	0.8
E (crossover function)	Single-Point	Two-Point	Uniform
F (mutation rate)	0.01	0.03	0.05

Table 2. Taguchi approach for experimental design using L_{27} orthogonal array

Design of Experiments	A	B	C	D	E	F	1	2	3	4	5	*Mean of f_i (km)*	*S/N*
1	1	1	1	1	1	1	f_1	f_2	f_3	f_4	f_5	315.8704	49.9902
2	1	1	1	1	2	2	f_1	f_2	f_3	f_4	f_5	315.4730	49.9791
3	1	1	1	1	3	3	f_1	f_2	f_3	f_4	f_5	321.2378	50.1360
4	1	2	2	2	1	1	f_1	f_2	f_3	f_4	f_5	313.9230	49.9354
5	1	2	2	2	2	2	f_1	f_2	f_3	f_4	f_5	315.2041	49.9706
6	1	2	2	2	3	3	f_1	f_2	f_3	f_4	f_5	320.5583	50.1175
7	1	3	3	3	1	1	f_1	f_2	f_3	f_4	f_5	316.6317	50.0092
8	1	3	3	3	2	2	f_1	f_2	f_3	f_4	f_5	320.8921	50.1269
9	1	3	3	3	3	3	f_1	f_2	f_3	f_4	f_5	323.0809	50.1859
10	2	1	2	3	1	2	f_1	f_2	f_3	f_4	f_5	318.3811	50.0588
11	2	1	2	3	2	3	f_1	f_2	f_3	f_4	f_5	320.5365	50.1169
12	2	1	2	3	3	1	f_1	f_2	f_3	f_4	f_5	323.3369	50.1929
13	2	2	3	1	1	2	f_1	f_2	f_3	f_4	f_5	318.2952	50.0552
14	2	2	3	1	2	3	f_1	f_2	f_3	f_4	f_5	320.4889	50.1162
15	2	2	3	1	3	1	f_1	f_2	f_3	f_4	f_5	323.6611	50.2018
16	2	3	1	2	1	2	f_1	f_2	f_3	f_4	f_5	318.0899	50.0496
17	2	3	1	2	2	3	f_1	f_2	f_3	f_4	f_5	320.0701	50.1046
18	2	3	1	2	3	1	f_1	f_2	f_3	f_4	f_5	322.9927	50.1838
19	3	1	3	2	1	3	f_1	f_2	f_3	f_4	f_5	320.5996	50.1191
20	3	1	3	2	2	1	f_1	f_2	f_3	f_4	f_5	322.1891	50.1622
21	3	1	3	2	3	2	f_1	f_2	f_3	f_4	f_5	357.9203	50.2209
22	3	2	1	3	1	3	f_1	f_2	f_3	f_4	f_5	320.8260	50.1250
23	3	2	1	3	2	1	f_1	f_2	f_3	f_4	f_5	322.0090	50.1571
24	3	2	1	3	3	2	f_1	f_2	f_3	f_4	f_5	324.7577	50.2312
25	3	3	2	1	1	3	f_1	f_2	f_3	f_4	f_5	319.7567	50.0956
26	3	3	2	1	2	1	f_1	f_2	f_3	f_4	f_5	320.9639	50.1289
27	3	3	2	1	3	2	f_1	f_2	f_3	f_4	f_5	322.5723	50.1725

Table 3. Signal-to-noise ratios of genetic algorithm parameter levels

Parameter	Level		
	1	2	3
A	50.05009	50.11998	50.15694
B	50.10846	50.10111	50.11744
C	50.10629	50.08768	50.11744
D	50.09728	50.09597	50.13377
E	50.04868	50.09583	50.18250
F	50.10683	50.09609	50.12409

is considered a measure of robustness. *S/N* evaluates five individual results to present the quality characteristics, which are represented as:

$$\frac{S}{N} = -10 \log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{f_i^2}\right) \tag{8}$$

where, $n = 5$.

The *S/N* of individual parameter is measured as per Eqn. (9). In the L_{27} orthogonal array table, for parameter A, the *S/N* values of levels 1, 2, and 3 are S/N_{A1}, S/N_{A2}, and S/N_{A3}, respectively.

Table 4. Analysis of variance table for L_{27} orthogonal array experiments

Parameter	DF	Seq. SS	Adj. SS	Adj. MS	F-value	*p*-value	% contribution
A	2	0.053005	0.053005	0.026502	54.73	0.000	32.09
B	2	0.001206	0.001206	0.000603	1.25	0.318	0.73
C	2	0.009358	0.009358	0.004679	9.66	0.002	5.66
D	2	0.008277	0.008277	0.004138	8.55	0.004	5.01
E	2	0.082954	0.082954	0.041477	85.65	0.000	50.22
F	2	0.003592	0.003592	0.001796	3.71	0.051	2.17
Residual error	14	0.006779					
Total	26	0.165172					

Seq. SS: Sequential sum of squares, Adj. SS: Adjusted sum of square, Adj. MS: Adjusted mean square.

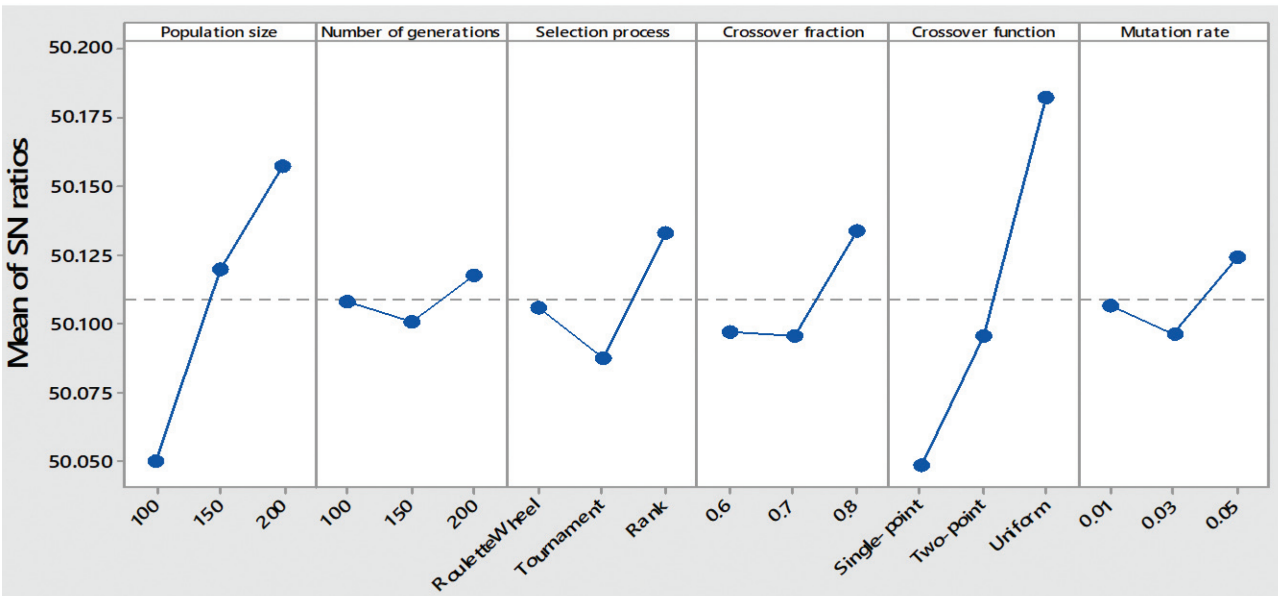

Figure 2. S/N response graph.

$$\left.\begin{aligned}\frac{S}{N_{A1}} &= \frac{1}{9}\left(\frac{S}{N_1}+\frac{S}{N_2}+\cdots+\frac{S}{N_9}\right)\\ \frac{S}{N_{A2}} &= \frac{1}{9}\left(\frac{S}{N_{10}}+\frac{S}{N_{11}}+\cdots+\frac{S}{N_{18}}\right)\\ \frac{S}{N_{A3}} &= \frac{1}{9}\left(\frac{S}{N_{19}}+\frac{S}{N_{20}}+\cdots+\frac{S}{N_{27}}\right)\end{aligned}\right\} \tag{9}$$

where, S/N_i is the signal-to-noise ratio of i^{th} run.

Based on the literature survey and availability of computation facility the GA parameters were selected and noted in Table 1, which portrays six GA parameters and their respective levels. To determine optimal GA parameters, 3^6 or 729 experiments need to be carried out. However, Taguchi design is utilised to conduct 27 experiments using the L_{27} orthogonal array table. Table 2 shows the mean of fitness values (f_i) varies in the range between 313.9230 and 357.9203 km. The largest *S/N* value is the optimal level of GA parameters, and the *S/N* ratios achieved are tabulated in Table 3. It is noticed that level 3 is the optimum level of all GA parameters. According to Table 1, the optimal GA parameters are rank selection, uniform crossover, population size (200), number of generations (200), crossover fraction (0.8), and mutation rate (0.05).

Analysis of variance (ANOVA) is carried out to establish the prominent control parameters in a precise manner by comparing the significance of GA parameters. Table 4 reveals the output of the ANOVA. It includes numerous statistics such as errors, degree of freedom (DF), control factors, means squares (MS), the sum of squares (SS), *p*-value, Fischer's F distribution (F-value), and contribution percentage of control factors. Where F-value is the two variances ratio and is called the F-test. Variances are the measure of scattering of data from the mean value. The importance of each control factor in an ANOVA is evaluated using F values. These tables are calculated with a 95% level of confidence. It is observed that the crossover function (85.65) and population size (54.73) possess larger F-values and have a significant effect on GA performance.

p-value assists in elucidating the significance of results in a statistical test for acceptance or rejection of the null hypothesis. When the *p*-value for the control factor is > 0.05, it is considered a non-significant factor. Therefore, number of generation (*p*-value = 0.318) and mutation rate (*p*-value = 0.051) are not significant parameters. However, crossover function and population size are significant parameters. The percentage contribution shows a measure of control parameters' effect on GA performance. The contribution of population size, number of generations, selection, crossover fraction, crossover function, and mutation rate for maximising gliding range is 32.09 %, 0.73 %, 5.66 %, 5.01 %, 50.22 %, and 2.17 %, respectively. The error percentage (4.10 %) is considerably small.

Visual summaries of the GA parameter's effect on optimisation performance and relationships between the factors and *S/N* are graphically shown in Figure 2. The dot illustrates the importance of individual control factors towards optimisation performance and *S/N* resonate quality of level. Lines in Fig. 2 that connect between levels could clearly show the impact of each control factor. It is noticed that factor E possesses the highest variance indicating crossover function is a prime factor for determining GA performance.

3.1.1 The Anticipated Optimum S/N

$$\frac{S}{N_{Predicted}} = \frac{\bar{S}}{N_{mean}} + \left(\frac{S}{N_{Ai}} - \frac{\bar{S}}{N_{mean}}\right) + \left(\frac{S}{N_{Bj}} - \frac{\bar{S}}{N_{mean}}\right) + \left(\frac{S}{N_{Ck}} - \frac{\bar{S}}{N_{mean}}\right) + \left(\frac{S}{N_{Dl}} - \frac{\bar{S}}{N_{mean}}\right) + \left(\frac{S}{N_{Em}} - \frac{\bar{S}}{N_{mean}}\right) + \left(\frac{S}{N_{Fo}} - \frac{\bar{S}}{N_{mean}}\right)$$

where,

$$\frac{\bar{S}}{N_{mean}} = \frac{1}{27}\sum_{i=1}^{27}\frac{S}{N_i}$$

S/N_{Ai}, S/N_{Bj}, S/N_{Ck}, S/N_{Dl}, S/N_{Em}, and S/N_{Fo} are the signal-to-noise ratio value for optimal level parameters A, B, C, D, E, and F, respectively.

3.1.2 Verification

The *S/N* value obtained is 51.2518 when optimal GA parameters are utilised and is approximately equal to the anticipated *S/N* value. Experimenting 5 times using GA optimal parameters fitness values are 362.7155, 365.1041, 360.6219, 365.2845, and 367.9889 km. The average fitness value of 364.3430 km is relatively near to the optimum expected glide range of 364.8670 km and the standard deviation is 2.5001, also trivial. Selected optimal parameters of GA using Taguchi design could able to decrease the randomness in fitness values and increase potency in searchability.

3.2 Artificial Neural Network

Artificial Neural Network (ANN) approach is an extremely dedicated computational technique possessing the potential to explore the relation between process input and output responses[63-64]. ANN consists of neurons that are arranged in input, hidden, and output layers. The information is received from input layer neurons, hidden layer estimates the relationship between variables and calculates the assigned weight of each variable as hidden layer neurons are fully linked to each neuron in both the input and output layer. Finally, the predicted results are produced by the output layer.

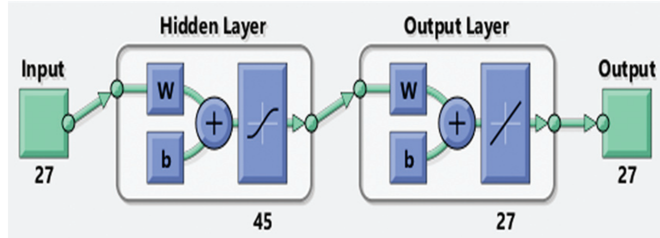

Figure 3. ANN architecture.

MATLAB neural network toolbox is employed for the study. Figure 3 shows the ANN architecture with both input and output layers having 27 neurons and a hidden layer possessing 45 neurons. The output responses and signal-to-noise ratio values achieved from the Taguchi design of experiments were verified using ANN. Data for training, testing, and validation was separated in the ratio 70:15:15. The Lavenberg-Marquardt backpropagation algorithm was selected for ANN as the training function. The backpropagation algorithm learns input-output relations during the training process. In the training process inputs are propagated to the hidden layer, sensitivities are backpropagated to minimize error and finally, the weights are updated. To develop a nonlinear relation between input and output, a hyperbolic tangent sigmoid function (tansig) was chosen as the activation function for all the layers.

ANN model was utilised to predict the S/N ratio based on experimental results obtained using the Taguchi method

Table 5. ANN predicted *S/N* values

Parameter	Level		
	1	2	3
A	50.06976	50.04152	50.14125
B	49.94822	50.11747	50.17193
C	50.04375	50.03685	50.17193
D	49.96653	50.09210	50.19389
E	50.01286	50.05865	50.18102
F	50.02314	50.09493	50.13446

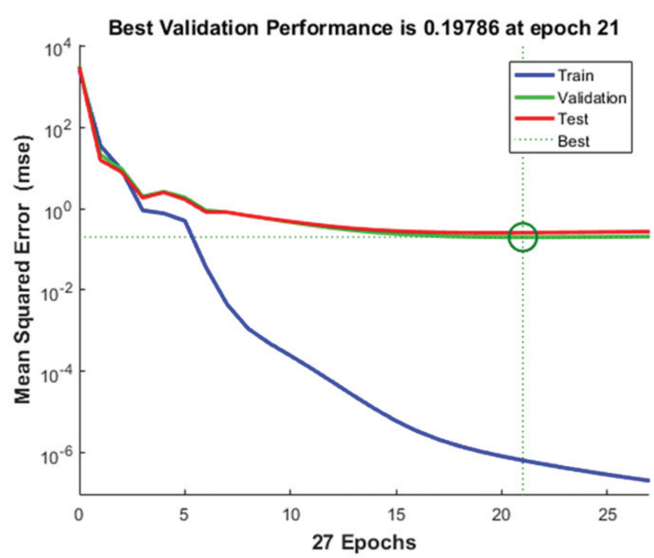

Figure 4. Validation performance of the neural network.

and ANOVA analysis (Table 5). It is also observed from the ANN model that level third is the optimum level of all GA parameters. The results obtained from the Taguchi method and ANOVA analyses are in good agreement with ANN predicted results. Figure 4 displays the performance graph of the ANN approach, showing variations in errors of training, validation, and testing for several epochs. The circle present in Fig. 4 infers the ultimate performance validation. The mean squared error (MSE) is found to be 0.19786 at the 21st epoch which is very small.

Figure 5 shows the gradient epoch of neural network performance, showing variation in Levenberg's damping aspect, performance gradient, and validation analysis. It is

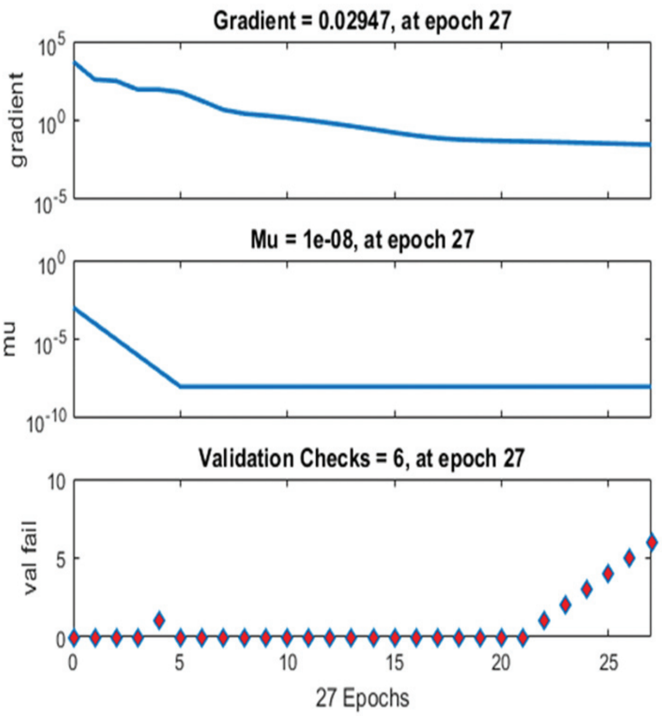

Figure 5. Gradient epoch of neural network performance.

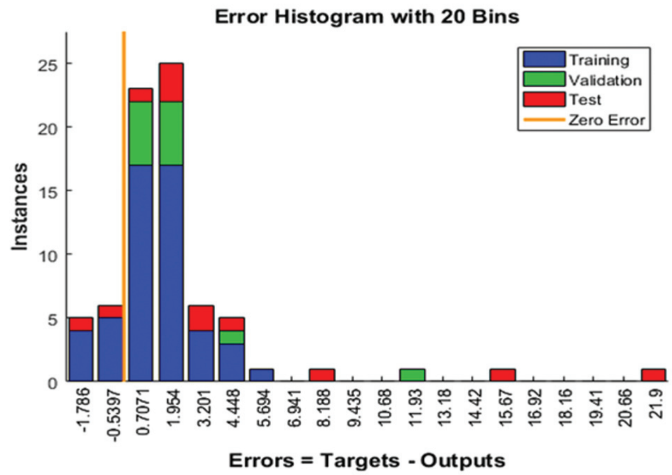

Figure 6. Error histogram of neural network.

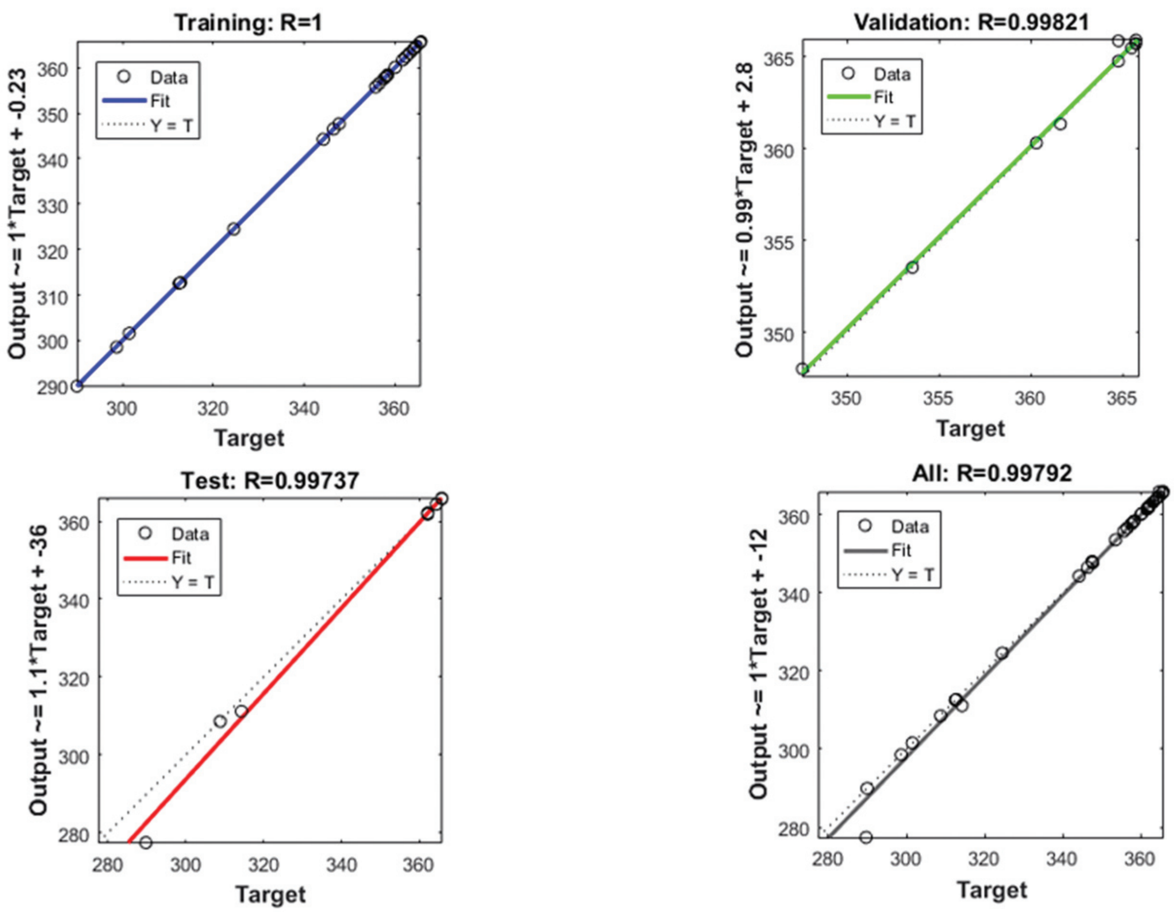

Figure 7. Neural network linear regression analysis graphs.

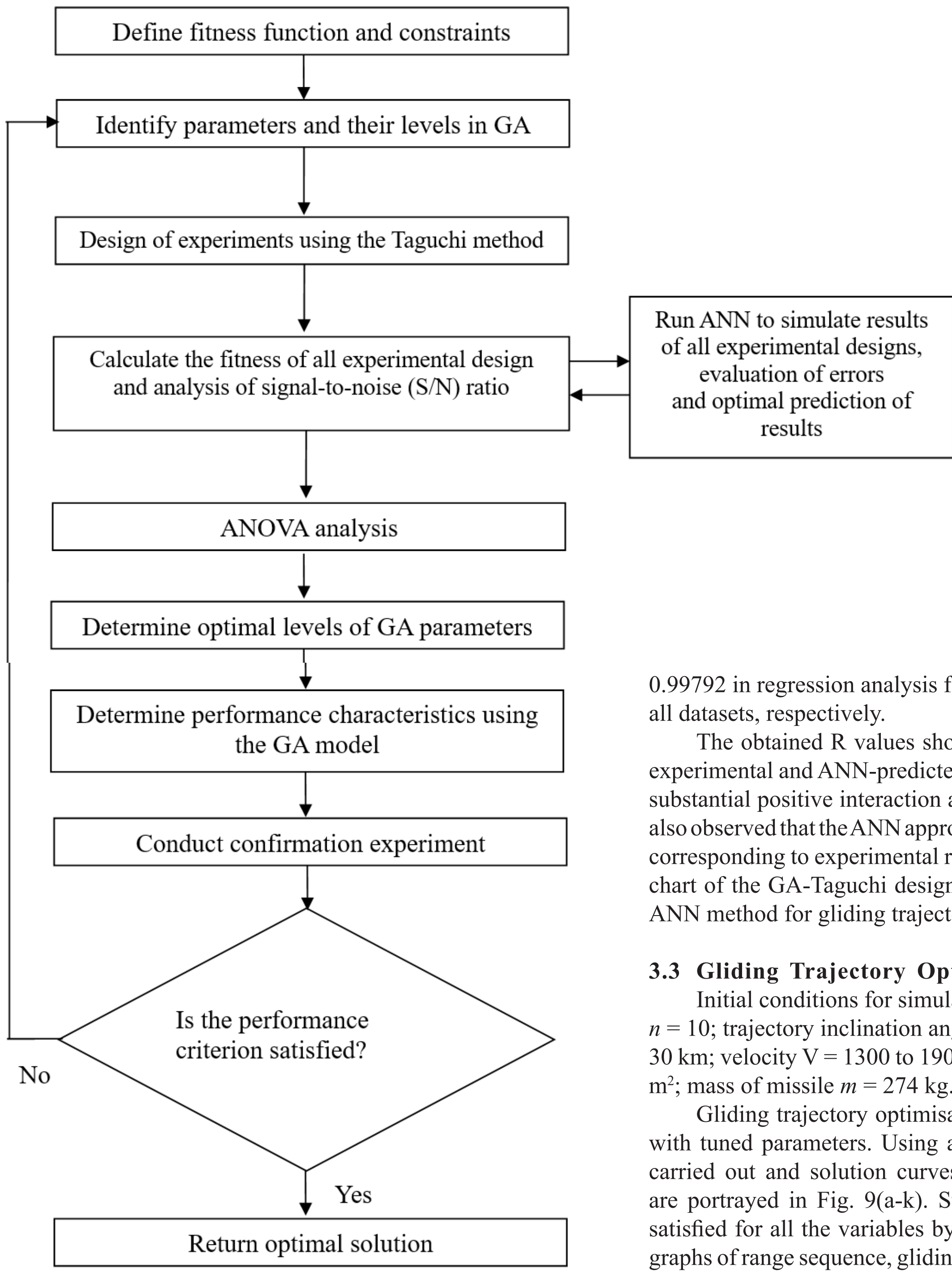

Figure 8. Flowchart of GA-Taguchi design of experiments-ANOVA-ANN method for gliding trajectory optimisation.

noticed that the mu factor was 0.00000001 and the gradient value was decreased at the 27th epoch to 0.02947. Moreover, the training of network was terminated at the 27th epoch taking account of 6 more validation analyses following the ultimate performance validation. The error histogram achieved in the ANN approach is displayed in Fig. 6. It is observed that the errors are distributed around zero in an acceptable range. Figure 7 shows the regression graphs for train, validation, test, and all data obtained from the ANN approach. The correlation coefficients (R) are found to be 1, 0.99821, 0.99737, and 0.99792 in regression analysis for training, test, validation and all datasets, respectively.

The obtained R values show a good correlation between experimental and ANN-predicted values. The result indicates a substantial positive interaction among inputs and outputs. It is also observed that the ANN approach provides precise responses corresponding to experimental results. Figure 8 displays a flow chart of the GA-Taguchi design of the experiments-ANOVA-ANN method for gliding trajectory optimisation.

3.3 Gliding Trajectory Optimisation

Initial conditions for simulation: dimension of population n = 10; trajectory inclination angle $\theta_0 = 10^o$; altitude h_0 = 23 to 30 km; velocity V = 1300 to 1900 m/s; reference area s = 0.302 m^2; mass of missile m = 274 kg.

Gliding trajectory optimisation was conducted using GA with tuned parameters. Using available data, simulations are carried out and solution curves for maximum gliding range are portrayed in Fig. 9(a-k). State terminal constraints were satisfied for all the variables by adequate accuracy. There are graphs of range sequence, gliding trajectory, velocity sequence, altitude versus time, AOA versus time, flight path angle versus time, altitude versus velocity, glide range versus velocity, flight path angle versus velocity, flight path angle versus range, and altitude versus flight path angle in Fig. 9. It is noticed that GA with optimised parameters met all the flight and terminal constraints. Figure 9(a) shows the range sequence and Fig. 9(b) shows the optimised gliding trajectory. It is illustrated in Fig. 9(a) and Fig. 9(b) that the optimal range obtained with GA is 367.9889 km. The initial height is 29.236 km which reaches the ground in the gliding phase. Additionally, while approaching from the middle of trajectory towards end, the altitude raised rapidly. This could be attributed to the available resource that can help increase the flight range of missiles. The flying time of

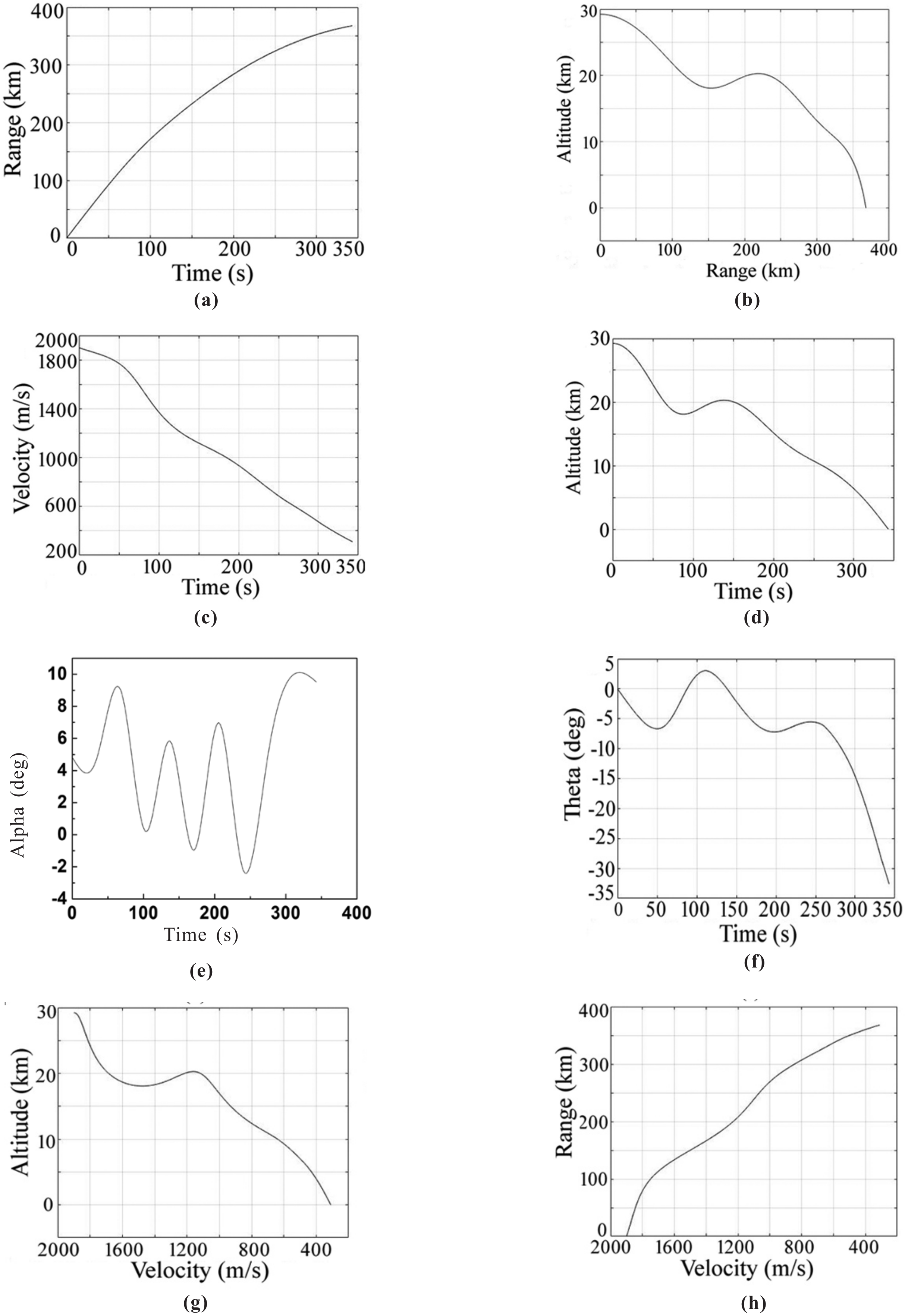

Figure 9. (a) range sequence, (b) gliding trajectory, (c) velocity sequence, and curves of (d) altitude versus time, (e) angle of attack versus time, (f) flight path angle versus time, (g) altitude versus velocity, and (h) range versus velocity.

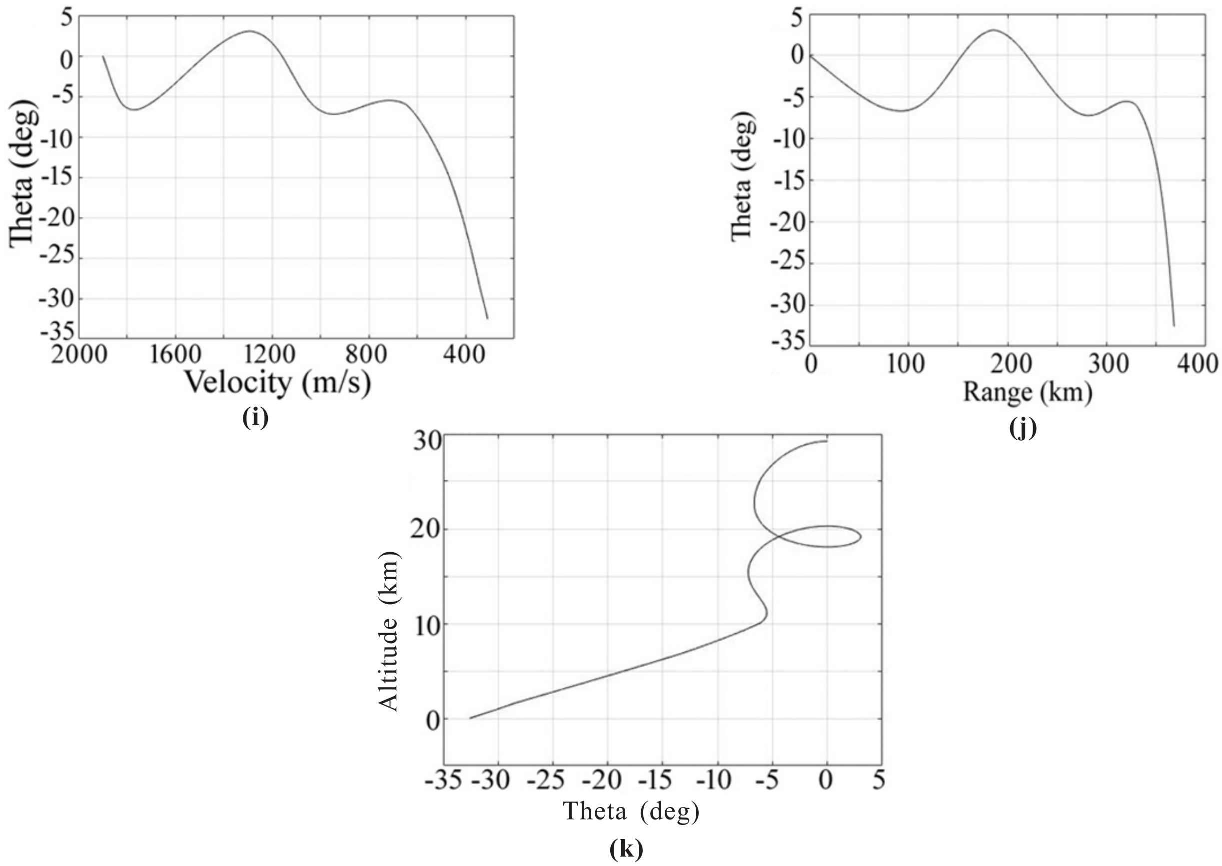

Figure 9. (i) Flight path angle versus velocity, (j) Flight path angle versus range, and (k) Altitude versus flight path angle.

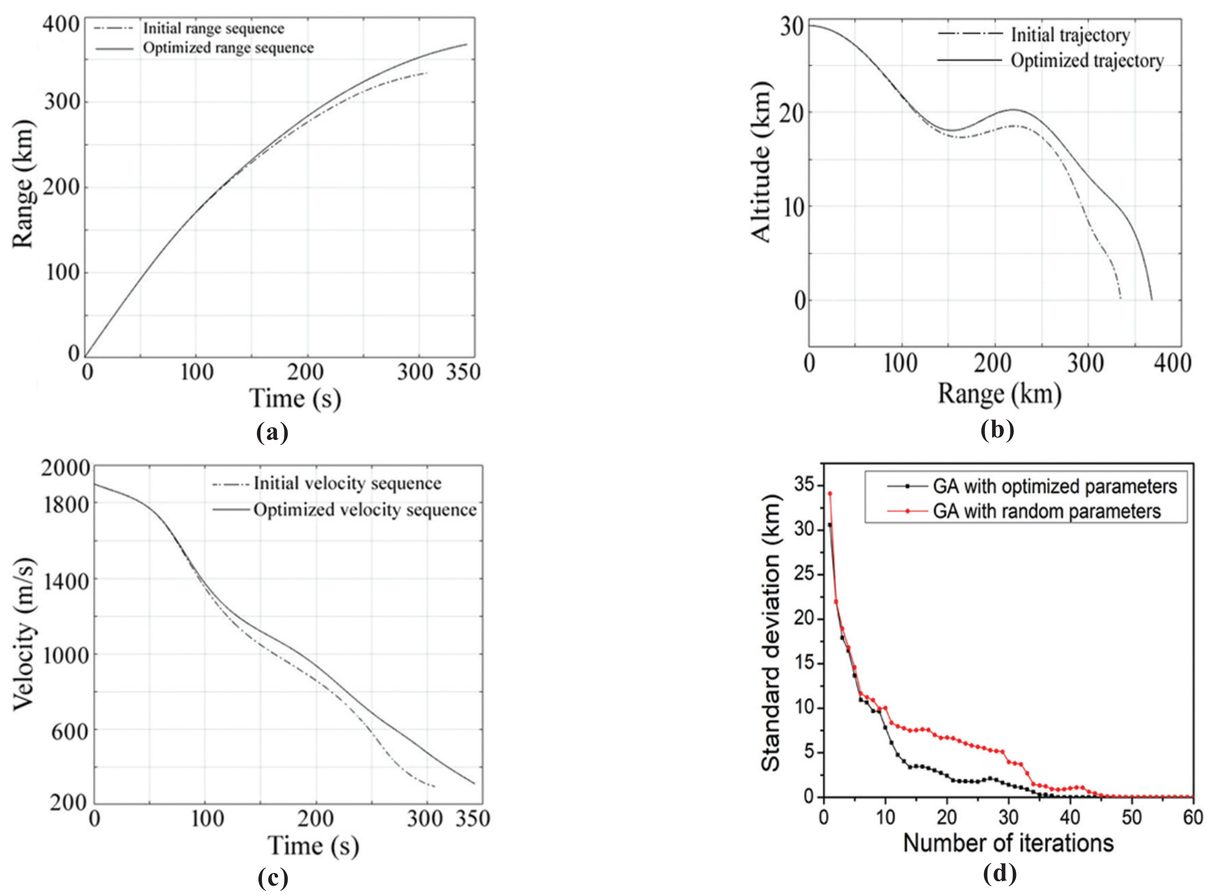

Figure 10. Comparison curves of (a) Range sequence, (b) Gliding trajectory, (c) Velocity sequence, and (d) Convergence graph.

the missile is found to be 342.7s. Smooth trajectory is observed during the entire missile flight indicating the correct phase flying of missile.

Figure 9(c) presents the velocity sequence of the gliding trajectory that starts from an initial velocity of 1900 m/s and reached the ground with a velocity of 310 m/s as a result of increasing potential energy. Figure 9(e) shows time histories of AOA that varied throughout the gliding stage. It is also observed from Fig. 9(e) that the control parameter (AOA) is within the constrained boundary -10^o to +10^o. ensuring acceptable aerodynamic behavior. AOA increased significantly at the end of the flight which promotes extending the gliding range through effective utilisation of existing missile kinetic energy. The results are in agreement with the physical aspect of the missile. The proposed optimisation procedure in this work offered a satisfactory solution to the gliding trajectory optimisation problem. The range of the missile could be increased by optimising the gliding trajectory. It is observed from the altitude versus velocity (Fig. 9(g)) and range versus velocity (Fig. 9(h)) profiles that final trajectory conditions are contented by good certainty. Flight path angles endure to be smaller in proportion that is a usual characteristic of gliding projectiles (Fig. 9(i-k)).

3.4 Comparative Study

Initially, gliding trajectory was optimised employing GA with tournament selection, two-point crossover and other parameters like population size, number of generations, crossover fraction and mutation rate are 200, 200, 0.8, and 0.01, respectively. Results obtained were compared with the optimised results achieved using GA with tuned parameters. Comparison curves of range sequence, velocity sequence, gliding trajectory, and convergence graphs were portrayed in Fig. 10 (a-d). It is observed that the obtained optimal range (367.9889 km) is increased by 10.02 % when compared to the earlier trajectory of 334.4702 km. Additionally, an increase in flying time (342.7s) is also observed compared to the earlier experiment (306.8 s). The convergence graphs of GA with random parameters and optimised parameters are displayed in Fig. 10(d). Convergence graphs indicate the decrease in standard deviation in range with several iterations until convergence. GA with optimised parameters converged faster at the 38th iteration when compared to GA with random parameters at the 49th iteration.

3.5 Nominal Trajectories

Various scenarios are used to check GA with tuned parameters and the experimental results obtained were recorded in Table 6. It is observed that a decrease in initial altitude from

Table 6. Test scenarios and results under various cases

Case	1	2	3	4
Initial altitude (km)	29.236	27.110	25.345	23.724
Initial velocity (m/s)	1900	1710	1545	1325
Simulation results				
Gliding distance (km)	367.9889	304.6486	250.2835	193.6259
Flying time (s)	342.7	310.2	263.8	238.5

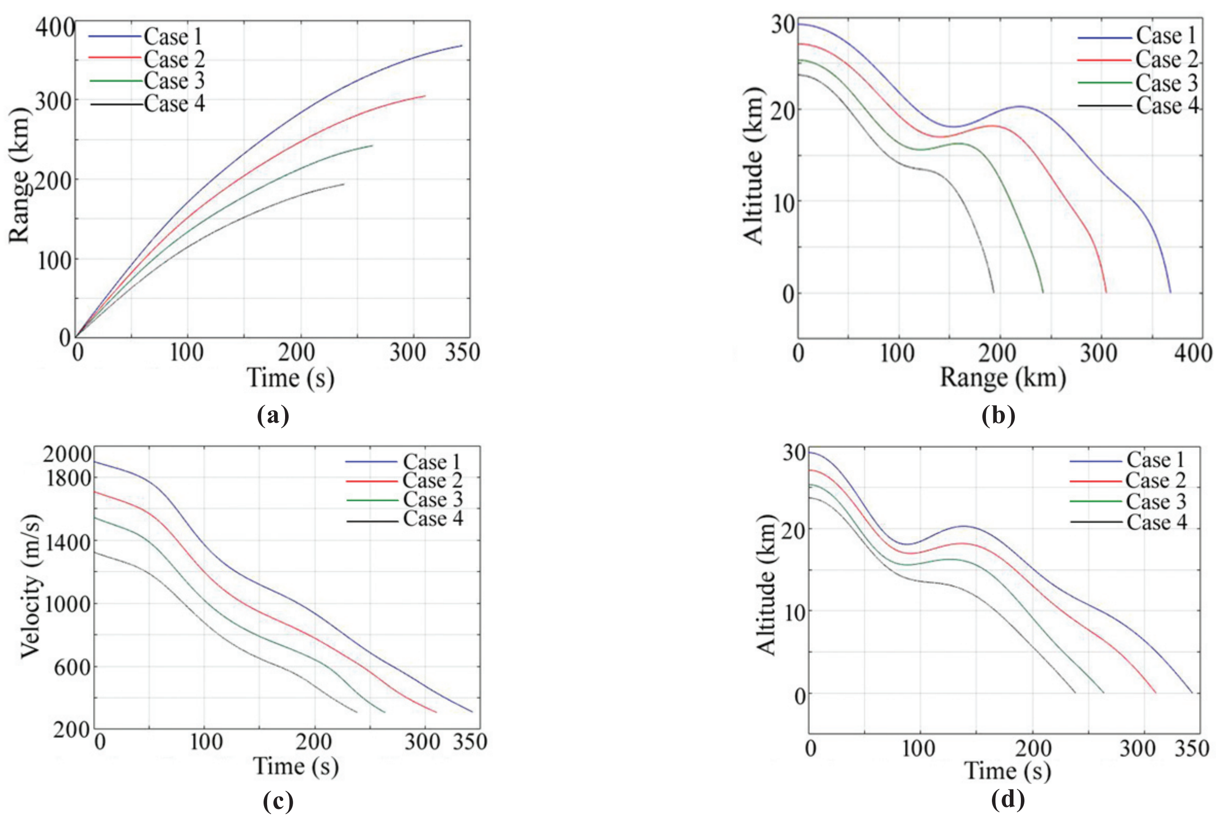

Figure 11. (a) Range sequence, (b) Gliding trajectory, (c) Velocity sequence, and (d) Altitude-time curves of various test scenarios.

Table 7. The computation time of different test case scenarios

Test case scenarios	1	2	3	4
Experimental runs	**Computation time (s)**			
1	76829	55786	51562	45322
2	73876	56215	52554	40115
3	70684	55345	49176	39926
4	72658	54853	50784	42311
5	73398	57011	51274	41751
Average	73489	55842	51070	41885

Table 8. Test cases and results under different scenarios with varying missile mass and drag coefficient.

Case	5	6	7	8
Missile mass (kg)	274	294	274	274
Drag coefficient (C_D)	Nominal	Nominal	10 % increase in nominal value	10 % decrease in nominal value
Results				
Gliding range (km)	367.9889	364.6310	341.9177	402.0607
Flying time (s)	342.7	335.2	319.5	369.1

29.236 km to 23.724 km and initial velocity from 1900 m/s to 1325 m/s resulted in a decrease in gliding range from 367.9889 km to 193.6259 km and flying time from 342.7s to 238.5s. Figure 11 (a-d) illustrates the results accomplished from various test scenarios. It is observed from the experimental results that terminal constraints are well-contented in all cases and flight states could successively emerge to the defined values.

3.6 Performance Analysis

The GA-Taguchi design of experiments-ANOVA-ANN method for trajectory optimisation is computationally inexpensive. The performance of the proposed method was evaluated by performing 5 different experiments of 4 test case scenarios and noting the computation time in Table 7. The computation time of test case scenarios was compared and observed that scenario 1 has high complexity with an average computation time of 73489 s. However, scenario 4 with an average computation time of 41885 s has the least complexity. The experimental results show that with a decrease in initial velocity and altitude computational complexity decreases along with the missile's gliding range.

3.7 Model Uncertainty

Four different test scenarios varying missile mass and coefficient of drag (C_D) are utilised to study the model uncertainty and results are tabulated in Table 8. It is observed that when missile mass increased from 274 kg to 294 kg with nominal C_D the gliding distance reduced from 367.9889 km to

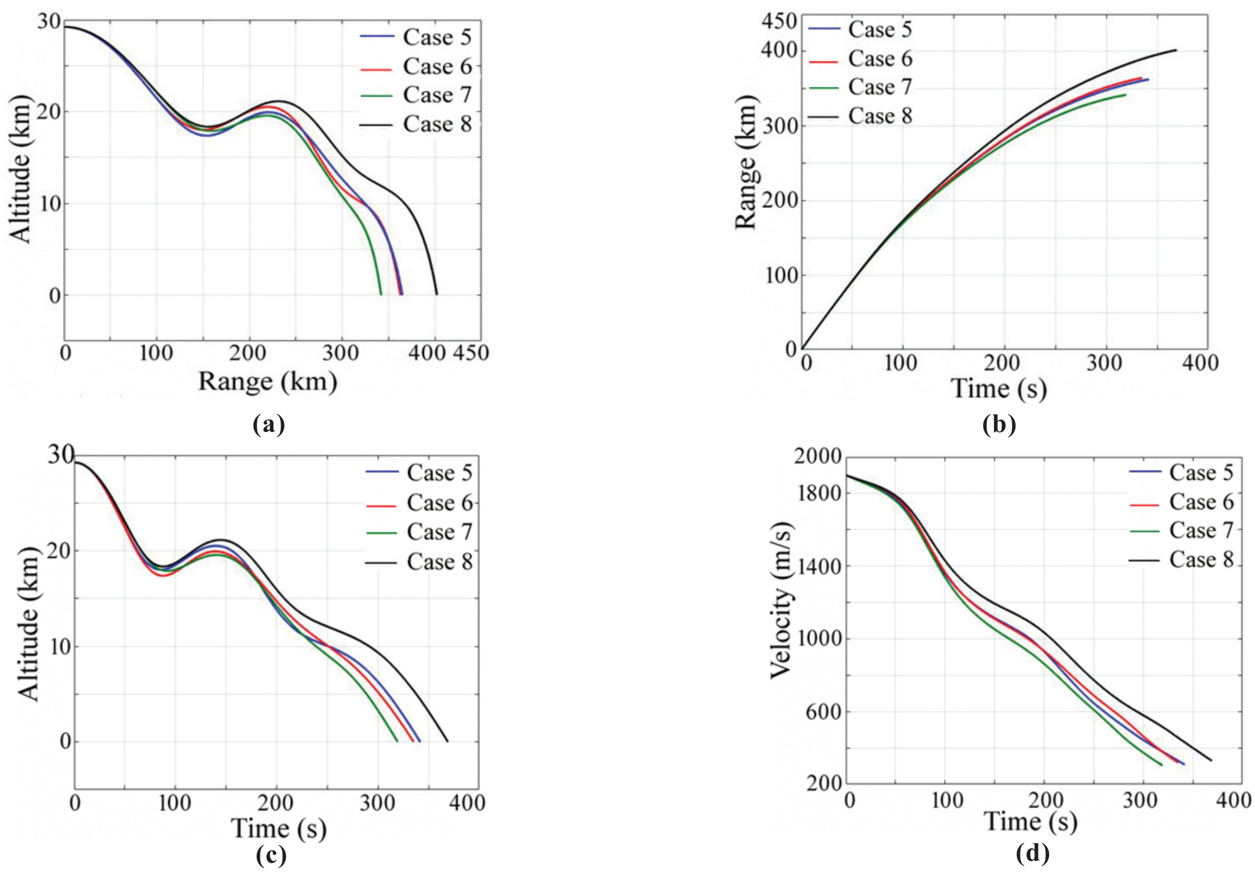

Figure 12. (a) Gliding trajectory, (b) Range sequence, (c) Altitude versus time graphs, and (d) Velocity sequence of various test cases with varying missile mass and coefficient of drag.

364.6310 km with flight time reduced from 342.7 s to 335.2 s. The increase in C_D by 10 % while keeping the missile mass constant at 274 kg resulted in a decrease in both gliding range, 341.9177 km, and flying time, 319.5 s. However, the decrease in C_D by 10 % while keeping the missile mass constant at 274 kg resulted in increased gliding range, 402.0607 km, and flying time, 369.1 s. The experimental outputs from different test cases are portrayed in Figure 12(a-d). The experimental outputs affirm that the constraints in every test case are well-contented.

3.8 Performance Analysis

Performance evaluation of the proposed methodology was analysed by carrying out five different experimental runs of four different test case scenarios (5 to 8) and computation time was tabulated in Table 9. The computational time obtained was compared and found that the complexity is higher in scenario 8 with an average computation time of 73929 s and scenario 7 has the least complexity with an average computation time of 64028 s. It is observed that computational time decreases with an increase in C_D which resulted in a decrease in the gliding distance of the missile and flying time. The same has been observed with an increase in missile mass.

Table 9. The computation time of different test case scenarios with varying missile mass and drag coefficient.

Test case scenarios	5	6	7	8
Experimental runs	**Computation time (s)**			
1	76829	70086	64349	73422
2	73876	69484	63458	73037
3	70684	70109	64263	76018
4	72658	71535	62966	74216
5	73398	70026	65104	72952
Average	73489	70248	64028	73929

4. CONCLUSIONS

GA with optimal parameters was exploited for solving the missile trajectory optimisation problem to achieve a maximised gliding range. Taguchi's design of experiments (L_{27} orthogonal array), analysis of variance (ANOVA), and artificial neural network (ANN) technique is beneficial to obtain better selection, crossover, and mutation operations and consequently, enhance the performance of GA for gliding trajectory optimisation. The *S/N* provides a performance criterion for the robustness of GA that promotes for selection of suitable factors and their corresponding level. Experimental results also reveal the significant effect of crossover function on GA performance. The result predicted by the ANN model achieves precise responses and is in good agreement. The gliding trajectory of the missile was optimised using GA with tuned parameters such as population size (200), rank selection, uniform crossover, crossover fraction (0.8), mutation rate (0.05), and number of generations (200). The gliding range of the missile significantly increased (10.02 %) compared to the earlier one. The results from various test scenarios show that the constraints are well satisfied in all cases. The present study demonstrated the effectiveness of the GA-Taguchi design of experiments-ANOVA-ANN approach for gliding trajectory optimisation. Suitable parameter selection of optimisation algorithms should be an essential part of optimisation studies. The parameter configuration selection should be made corresponding to the present optimisation problem because the same parameter configuration may not be appropriate for other optimisation problems. The present research will be extended for the spherical earth model in the future.

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