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# EXTERNAL GEOMETRY AND FLIGHT PERFORMANCE OPTIMIZATION OF TURBOJET PROPELLED AIR TO GROUND MISSILES

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## ABSTRACT

The primary goal for the conceptual design phase of a generic air-to-ground missile is to reach an optimal external configuration which satisfies the flight performance requirements such as flight range, flight time, launch mass, stability and control effectiveness as well as geometric constraints imposed by the designer. This activity is quite laborious and requires the examination and selection among huge numbers of design alternatives.

This study is mainly focused on multi objective optimization techniques for an air-to-ground missile design by using heuristics methods namely as Non Dominated Sorting Genetic Algorithm and Multiple Cooling Multi Objective Simulated Annealing Algorithm. Furthermore, a new hybrid algorithm is also introduced using Simulated Annealing cascaded with the Genetic Algorithm in which the optimized solutions are passed to the Genetic Algorithm as the initial population. A trade off study is conducted for the three optimization algorithm alternatives in terms of accuracy and quality metrics of the optimized Pareto fronts.

## INTRODUCTION

In current aerospace applications, the conceptual design step calls for a critical part of the whole process. The reason behind this fact is that the designer should satisfy some several challenging requirements for maximum efficiency and performance at this stage. Design optimization then tries to find the maximum and minimum of design objectives which is a function of design variables. The design variables contribute to missile diameter, length, nose geometry, stabilizer size and geometry and the control surface size and geometry. As a result of this process, the optimum external geometry could be achieved and the optimum external geometry obtained is to be considered as initial baseline geometry for the further design processes of the whole missile system.

A simulation based external geometry optimization tool for the conceptual design phase of an air-to-ground missile is developed in this study. For this purpose, two heuristic optimization algorithm alternatives are examined: Simulated Annealing and Genetic Algorithm, since they are the most preferred techniques used for the multi-objective optimization in similar studies. In addition to this, a hybrid algorithm which is a synthesis of Simulated Annealing and Genetic Algorithm is employed and the results are examined in terms of computational time and solution accuracy.

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## METHOD

### Air-To-Ground Missile Model

Considering the accuracy and the computational performance of each alternative, the usage of a simulation loop to evaluate fitness function value of single missile geometry is thought to be better for this work. By this way, some flight performance parameters like range, longitudinal stability and controllability may be evaluated. At this stage of the design, it is aimed to obtain the optimal baseline missile geometry rather than a detailed one which is often necessary for the preliminary design stage at which much time is spent laboriously calculating the effects of various design parameters on the missile configuration. Therefore, the roll and yaw considerations of the missile are disregarded for the time being. The two degree of freedom model includes two translational motions that are the axial (range) and vertical (altitude) motions.

The two degrees of freedom model is comprised of sub models which are equations of motion, aerodynamics, propulsion and atmosphere models [1].

The required aerodynamic coefficients axial force coefficient ($C_A$) and normal force coefficient ($C_N$) are generated using Missile DATCOM 2008 executable program [2] as a function of angle of attack ($\alpha$), Mach number and elevator deflection angle ($C_A$ ($\delta_e$,$\alpha$,M) ) for a given missile external geometry. All other needed aerodynamic data is attained as a consequence of the linear interpolation of the available data for the given flight conditions.

Since the lateral effects are out of concept, the sideslip angle, $\beta$, is always set to 0 and the force and moment coefficients are evaluated at this value. Considering the flight conditions frequently encountered for a generic air-to-ground missile, the domain of the angle of attack, Mach number and elevator deflection angles, at which the aerodynamic data would be generated, are decided as below.

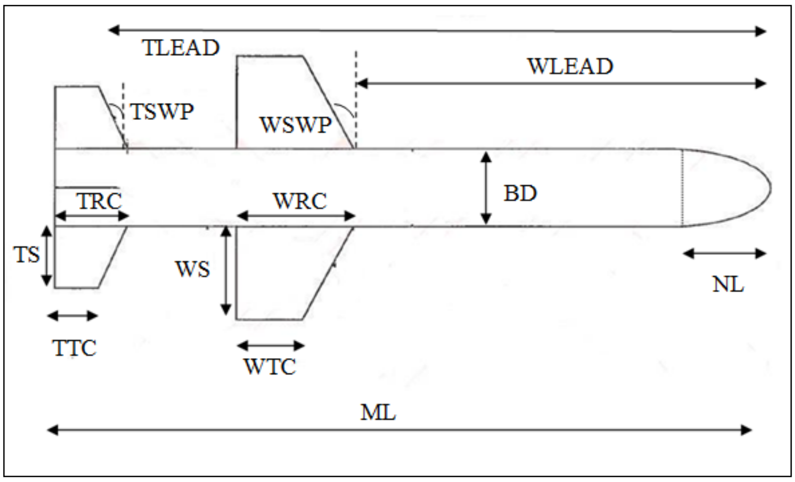
Angle of Attack = [-10, -7, -4, -2, 0, 2, 4, 6, 8, 10]

Mach = [0.1, 0.3, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1, 1.2]

Elevator Deflection Angle = [0, 5]

### Optimization Module

The geometrical parameters of the missile that should be taken into account as variables of the optimization problem are taken as in Figure 1.




| | |
|---|---|
| BD | Body Diameter |
| ML | Missile Length |
| NL | Nose Length |
| WS | Wing Span |
| WRC | Wing Root Chord |
| WTC | Wing Tip Chord |
| WSWP | Wing Sweep Angle |
| WLEAD | Wing Leading Edge |
| TS | Tail Span |
| TRC | Tail Root Chord |
| TTC | Tail Tip Chord |
| TSWP | Tail Sweep Angle |
| TLEAD | Tail Leading Edge |

Figure 1 Geometric Variables to be Optimized

### Single Objective Optimization

The objectives for single objective optimization are maximum flight range and minimum launch mass. The flight range is maximized with specified constraints as an initial effort. In addition, initial launch mass is imposed as a constraint into the optimization problem such that the launch weight of the optimized missile is forced to be less than the given upper limit for the missile weight. The sign of the range objective (since the range is to be maximized) is made negative in the fitness function.

The same procedure is followed for the mass objective. In that case, the missile initial mass is tried to be minimized while satisfying the given at least range constraint.

After all these adjustments, the composite fitness functions to be minimized for single objective optimization problem is obtained as follows where the penalty coefficients for missile launch weight and flight range are taken as $k_{mass} = 10^3$ and $k_{range} = 10^3$, respectively. No additional penalization is imposed on design variables.

$$FF_{rnge}(\bar{x}) = \frac{f_{range}(\bar{x})}{f_{range}^{*}} + k_{mass}\frac{max(0, f_{mass}(\bar{x}) - mass_u)}{f_{mass}^{*}} \quad (1)$$

$$FF_{mass}(\bar{x}) = \frac{f_{mass}(\bar{x})}{f_{mass}^{*}} + k_{range}\frac{max\left(0, range_L - f_{range}(\bar{x})\right)}{f_{range}^{*}} \quad (2)$$

$\bar{x}$ : The design vector including the geometry parameters.
$FF_{range}$: Fitness function for range objective
$FF_{mass}$: Fitness function for mass objective
$f_{range}$ : Range value evaluated for the current design set $\bar{x}$ [km]
$f_{range}^{*}$ : Range normalization factor [km]
$f_{mass}$ : Initial launch mass value evaluated for the current design set $\bar{x}$ [kg]
$f_{mass}^{*}$ : Initial launch mass normalization factor [kg]
$k_{range}$ : Penalty coefficient for flight range
$k_{mass}$ : Penalty coefficient for initial launch mass
$range_L$: Lower bound for flight range [km]
$mass_u$ : Upper bound for initial launch mass [kg]

The single objective missile design optimization problem is carried out by using Hide and Seek Simulated Annealing, Genetic Algorithm and a hybrid Simulated Annealing-Genetic Algorithm.

**Multi Objective Optimization**
In this study, two algorithms for multi-objective optimization are taken into consideration: Non-Dominated Sorting Genetic Algorithm (NSGA-II) and Multiple Cooling Multi Objective Simulated Annealing (MC-MOSA)

<u>Non Dominated Sorting Genetic Algorithm (NSGA-II):</u> For the solution of the multi-objective optimization problem, an improved version of Non-Dominated Sorting Algorithm (NSGA) is utilized called NSGA-II. This outperforms the previous version in terms of the diversity of the set of solutions and the convergence to the true Pareto optimal set [3]. The main advantage of the new approach is that there is no need to input any user defined parameter for the sake of maintenance of the diversity among the members of the population.

<u>Multiple Cooling Multi Objective Simulated Annealing (MC-MOSA):</u> The general approach is similar as in the case for Hide-Seek Simulated Annealing algorithm. The main difference is that a population of fitness functions are used to examine the test point function [4].

<u>Hybrid Algorithm (MC-MOSA + NSGA-II):</u> MC-MOSA and NSGA-II algorithms are merged into a hybrid algorithm to improve the convergence of the feasible solutions to the real pareto front. MC-MOSA algorithm is used as the first step. The obtained non-dominated points are made to pass to the NSGA-II algorithm as initial population.

## RESULTS

The two objective missile design optimization problem is solved using NSGA-II and hybrid algorithm and the results are presented in Figure 2 and Figure 3. (For both 1000 and 2000 number of function evaluations together with the results of MC-MOSA with the same number of function evaluations)

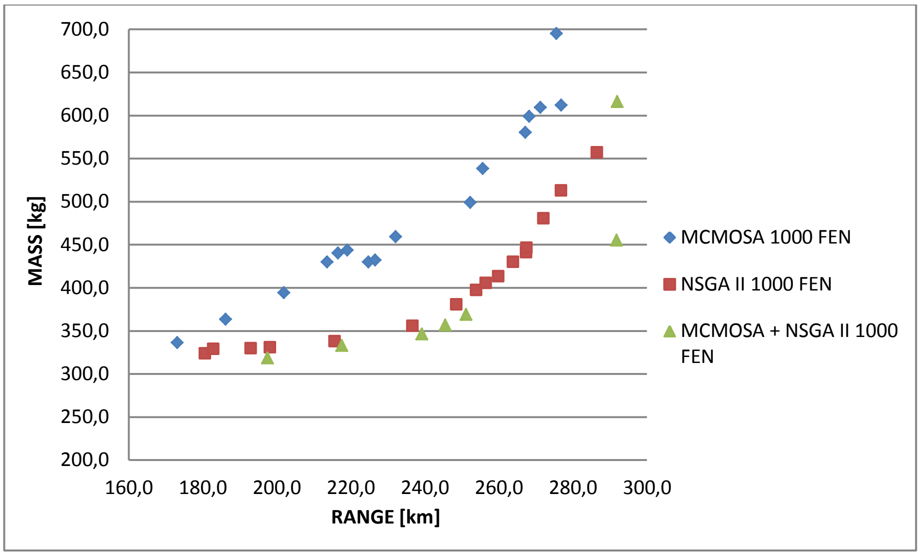



Figure 2 Missile Design Multi Objective Optimization Results after 1000 FEN

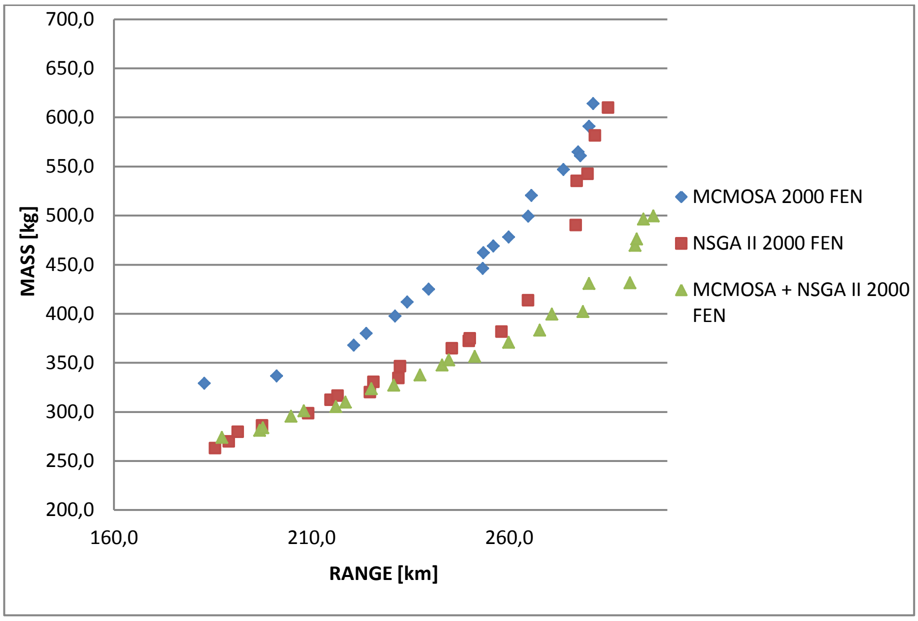



Figure 3 Missile Design Multi Objective Optimization Results after 2000 FEN

For the current problem, the Pareto front of NSGA-II algorithm looks better when compared with the front of MC-MOSA algorithm since it was able to find better optimal points for present objectives. Approximately two times longer computational time than the one for MC-MOSA algorithm is the payoff for better front, though. The hybrid algorithm, carried out for an ultimate trial, indicated the capability of the algorithm of finding more non-dominated points on the front that is closer to the optimal than other algorithms.

## References

[1] Fleeman, E. L. "*Tactical Missile Design*", AIAA Education Series, USA. 2001

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[3] Deb K., *Multi-objective Optimization Using Evolutionary Algorithms*, Wiley, New York, USA, 2001

[4] Tekinalp, O., Karsli, G., "A New Multi-objective Simulated Annealing Algorithm", Journal of Global Optimization, Vol. 39, No. 1, 49-77, Sep. 2007.

## APPENDIX

Multiple Cooling Multi Objective Simulated Annealing algorithm, developed by Tekinalp [4], is presented in this section.

The algorithm uses multiple linear or elliptic fitness functions. A set of linear fiteness functions may be written as follows:

$$FF_k = \sum_{i=1}^{N} w_{ki} f_i \qquad k = 1,2, \dots \dots R \tag{3}$$

$$\sum_{i=1}^{n} w_i = 1 \qquad i = 1,2, \dots \dots . N \tag{4}$$

R is the number of fitness functions and N is the numbers of objectives. The steps followed for MC-MOSA algorithm are listed below.

*Step 0*

Initialize random number generators. Generate the initial test point $x_0$ in the interior of S and choose a high enough temperature of $T_0$. Initialize the best and next best records of the fitness functions ($\check{F}^{best} = \check{F}^{nextbest} = 0$)

*Step 1*

*Search direction, $\theta^k$, on the surface of a unit sphere with uniform distribution and step size $\lambda^K$, are assigned randomly. Setting next variables as $y^k = x^k + \lambda^k \theta^k$*

*Step 2*

Generate $V^k \left(0 \leq V^k \leq 1\right)$ from uniform distribution

*Step 3*

Evaluate the probability acceptance function

$$Pr = min\left\{1, max\left[exp\left(\frac{\Delta\tilde{F}_m{}^K}{T_m{}^K}\right)\right]\right\}, \tag{5}$$

$$\Delta\tilde{F}_m{}^K = \tilde{F}_m(x^K) - \tilde{F}_m(y^K), \quad m = 1,2, \dots \dots M, \tag{6}$$

where $\tilde{F}_m$ is a set of linear fitness functions.

*Step 4*

Accept the trial point $y^K$, with probability Pr

$$x^{K+1} = \begin{Bmatrix} y^K \text{ if } V^K \in (0, \mathrm{Pr}) \\ x^K \text{ otherwise} \end{Bmatrix} \tag{7}$$

*Step 5*

If Pr = 1 (i.e., if there are any improving fitness functions, $\tilde{F}_m\left(y^K\right), (m = 1,2, \dots . M)$):

- Archive the test point ($x^{K+1} = y^K$), as well as values of the objectives, $\left(f_i(y^K)\right)$ , to be further processed to obtain the Pareto front.
- Update the best and next best records, $\tilde{F}_m{}^{nextbest} = \tilde{F}_m{}^{best}$ and $\tilde{F}_m{}^{best} = \tilde{F}_m(y^K)$
- Update the related temperature according to the annealing schedule below,

$$T = 2\left[\tilde{F}_m(x^{K+1}) - \tilde{F}_m{}^*\right] / \chi^2{}_{1-p}(d) \tag{8}$$

where $\tilde{F}_m^{\;*}$ is the global minimum of *m*th fitness function, and $\chi^2{}_{1-p}(d)$ is the 100(1-p) percentile point of the chi-square distribution with *d* degrees of freedom. Since the global minimum is not known in advance, its estimate $\tilde{F}^e{}_m$ is used instead as given below [41].

$$\tilde{F}^e{}_m \;=\; \tilde{F}_m^{\;best} \;+ \frac{\tilde{F}_m^{\;best} + \tilde{F}_m^{\;nextbest}}{(1-p)^{-d/2} - 1} \qquad (9)$$

The estimator may also be used with upper and lower bounds in the algorithm as:

$$\tilde{F}_m^{\;*} = \begin{Bmatrix} \tilde{F}_m^{\;lower}, & if,\; \tilde{F}^e{}_m < \tilde{F}_m^{\;lower} \\ \tilde{F}_m^{\;upper}, & if,\; \tilde{F}^e{}_m < \tilde{F}_m^{\;upper} \\ \tilde{F}^e{}_m & otherwise \end{Bmatrix} \qquad (10)$$

Increment the loop counter and go to Step1 until permitted number of function evaluations reached these steps.