Optimization of Specific Impulse of Scramjet Engine Using Nature Inspired Techniques

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Abstract

SCRAMJET is supersonic combustion ramjet engine, proposed by F. S. Billig in 1964. Scramjet engines are the potential candidates for the future hypersonic cruise vehicles, due their superiority in terms of specific impulse when compared to their conventional counter parts. Specific impulse is a measure of efficiency of an engine. Specific impulse is directly proportional to the range of a vehicle (Breguet's range equation). Maximizing specific impulse eventually maximizes the range. An attempt has been made here to optimize the specific impulse of scramjet engine for cruise Mach numbers ranging from 5.5 to 8 using the stream thrust analysis by nature inspired techniques. Altitude of scramjet engine operation , combustor inlet Mach number and exit to ambient pressure ratio are used as variables for the optimization problem. In the curent work two of the oldest and most generalized optimization techniques namely Genetic Algorithm, Particle Swarm Optimization and three new techniques namely Teaching Learning Based Optimization algorithm , Harmonic Search and Bat algorithm are compared. Results indicate that, specific impulse decreases with increase in freestream Mach number and flying at lower dynamic pressures i.e higher altitudes provides better engine performance irrespective of the freestream Mach number.

Keywords: Scramjet, Stream thrust analysis, Specific impulse, Nature Inspired Techniques

NOMENCLATURE

A	area	**Subscripts**	
F	thrust	o	ambient
f	fuel to air ratio	1	isolator inlet
g	acceleration due to gravity	3	combustor inlet
h	altitude	4	combustor exit
I	specific impulse	10	nozzle exit
M	Mach number	b	burner
$\dot{m}$	mass flow rate	c	compression
P	static pressure	e	expansion
Q	heat of reaction	s	stochiometry
q	dynamic pressure		
R	universal gas constant	**Symbols**	
S	stream thrust function	η	efficiency
T	static temperature	γ	ratio of specific heats
V	velocity	ϕ	equivalance ratio

1 INTRODUCTION

SCRAMJET is a supersonic combustion ramjet engine, where there are no rotating parts as in turbojet or turbofan engines and it uses shock waves and expansion fans to compress and expand the airflow respectively. Hypersonic air breathing cruise vehicle (> Mach 5) will become a reality after realizing such an engine. The prime difference between a ramjet and scramjet engine is that combustion takes place at subsonic speeds in ramjet while combustion takes place at supersonic speeds in scramjet's. Ramjet's are considered to be efficient in the flight Mach number range of 2-4 but beyond this flight Mach number, a huge amount of total pressure loss is incurred while bringing the Mach number down to subsonic speeds in the combustion chamber. Moreover due to the presence of terminating normal shock at the end of the ramjet inlet, temperature shoots up causing dissociation of air molecules leading to inefficient combustion. Therefore there is a loss in performance of the engine. On the other hand the scramjet engine does not have a terminating normal shock, rather a series of oblique shocks which has a lower total pressure loss and lower combustor inlet temperature compared to ramjets by maintaining supersonic speed at combustor entry. Scramjet engines are air breathing engines i.e they use atmospheric oxygen for combustion whereas conventional rockets carry onboard oxidizers due to which scramjets are more efficient than conventional rockets. The concept of supersonic combustion ramjet engine was proposed by F. S. Billig in 1964 [1]. Since then many conceptual designs of hypersonic cruise vehicles, single space to orbit(SSTO) and two stage to orbit(TSTO) vehicles were proposed, due the superiority of scramjet engines in terms of specific impulse when compared to their counter parts. In the preliminary design of scramjet engines thermodynamic cycle analysis are used to compute the engine parameters. In 1979 E. T. Curran, et al studied the use of stream thrust concepts for approximate evaluation of scramjet performance [2]. This analysis is being used as an effective tool for computing engine parameters in the preliminary design phase. K. G. Bowcutt developed a method to optimize the aeropropulsive performance of a hypersonic scramjet powered vehicle using idealized inviscid aerodynamics by a non linear simplex method to emphasize on the level of interdependence between the disciplines involved in the design of scramjet engines [4]. R. J. Hartfield et. al., used first order modeling principles to optimize the scramjet powered missile using GA for a given flight condition to indicate the narrow flight envelope of a scramjet engine [5]. Kristen N. Roberts et. al., used stream thrust analysis to design a hypersonic scramjet engine with a startin Mach number of 4 [8]. However, optimization of scramjet engine incorporating altitude as a variable has been seldom reported. An attempt has been made here to optimize the specific impulse of scramjet engine for cruise condition incorporating altitude as a design variable, using nature inspired evolutionary algorithms.

2 OPTIMIZATION OF SCRAMJET ENGINE

2.1 The objective function - Specific Impulse

The objective function to be maximized in the current work is specific impulse. Specific impulse is a measure of efficiency of an engine. It is defined as the thrust produced per unit weight flow rate of the fuel. Specific impulse is directly proportional to the range of a vehicle(Breguet's range equation). Maximizing specific impulse eventually maximizes range.

2.2 The mathematical model - Stream thrust analysis

In the current work stream thrust analysis is used for computing the specific impulse. Stream thrust analysis is a one dimensional flow analysis which leans heavily on momentum relationships and accounts for mass, momentum and kinetic energy fluxes contributed by the fuel, geometry of the burner, and exhaust flows that are not matched to the ambient pressure. It uses the entire set of control volume conservation equations to compute the engine parameters [3]. The control volume used here is shown in Figure 1. Fuel used in this analysis is JP - 7 [6]. The heating value (Q_R) and the stochiometric fuel to air ratio (f_s) of the fuel are 43.9 MJ/kgK and 0.0674 respectively. The analysis was carried out for an equivalance ratio of 0.75. The equations used to calculate the specific impulse are given below.

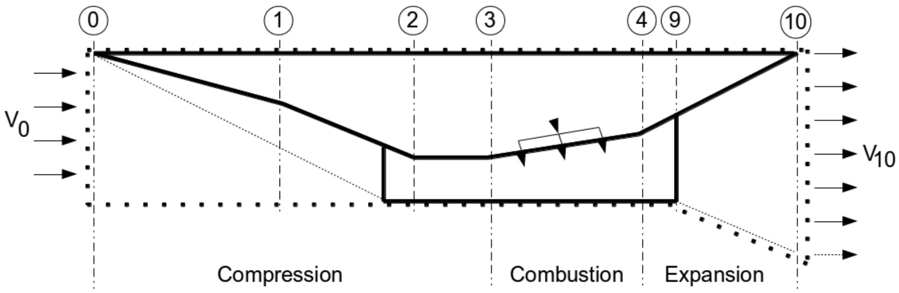

Figure 1: Control volume definition [3]

Compression

1. Stream thrust function at freestream conditions

$$S_{ao} = V_o(1 + \left(\frac{RT_o}{V_o^2}\right) \tag{1}$$

2. Combustor entrance temperature

$$T_3 = T_o \left(\frac{1 + \frac{\gamma_c - 1}{2} M_o^2}{1 + \frac{\gamma_c - 1}{2} M_3^2}\right) \tag{2}$$

3. Combustor entrance velocity

$$V_3 = \sqrt{V_o^2 - 2C_{pc}T_o\left(\frac{T_3}{T_o} - 1\right)} \tag{3}$$

4. Stream thrust function at combustor entrance

$$S_{a3} = V_3(1 + \left(\frac{RT_3}{V_3^2}\right) \tag{4}$$

5. Ratio of combustor entrance pressure to freestream pressure

$$\frac{P_3}{P_o} = \left\{\frac{\frac{T_3}{T_o}}{\frac{T_3}{T_o}(1 - \eta_c) + \eta_c}\right\}^{\frac{C_{pc}}{R}} \tag{5}$$

6. Ratio of combustor entrance area to freestream entrance area

$$\frac{A_3}{A_o} = \frac{T_3}{T_o}\frac{P_o}{P_3}\frac{V_o}{V_3} \tag{6}$$

Combustor

1. Combustor exit velocity

$$V_4 = V_3\left\{\frac{1 + f\frac{V_{fx}}{V_3}}{1 + f} + \frac{C_f\frac{A_w}{A_3}}{2(1 + f)}\right\} \tag{7}$$

2. Combustor exit temperature

$$T_4 = \frac{T_3}{1 + f}\left\{1 + \frac{1}{C_{pb}T_3}\left[\eta_b f Q_R + f C_{pb} T^0 + \left(1 + f\frac{V_f^2}{V_3^2}\right)\frac{V_3^2}{2}\right]\right\} - \frac{V_4^2}{2C_{pb}} \tag{8}$$

3. Ratio of area at combustor exit to combustor entrance

$$\frac{A_4}{A_3} = \frac{T_4}{T_3}\frac{V_3}{V_4}(1+f) \tag{9}$$

4. Stream thrust function at combustor exit conditions

$$S_{a4} = V_4(1 + \left(\frac{RT_4}{V_4^2}\right) \tag{10}$$

Expansion

1. Temperature at engine exit

$$T_{10} = T_4\left\{1 - \eta_e\left[1 - \left(\frac{P_{10}}{P_o}\frac{P_o}{P_4}\right)^{\frac{R}{C_{pe}}}\right]\right\} \tag{11}$$

2. Velocity at engine exit

$$V_{10} = \sqrt{V_4^2 + 2C_{pe}(T_4 - T_{10})} \tag{12}$$

3. Stream thrust function at engine exit conditions

$$S_{a10} = V_{10}(1 + \left(\frac{RT_{10}}{V_{10}^2}\right) \tag{13}$$

4. Ratio of area at engine exit to area at freestream entrance

$$\frac{A_{10}}{A_o} = \frac{T_{10}}{T_o}\frac{P_o}{P_{10}}\frac{V_o}{V_{10}}(1+f) \tag{14}$$

Overall engine performance

1. Specific thrust

$$F_s = \frac{F}{\dot{m}} = (1+f)S_{a10} - S_{ao} - \frac{RT_o}{V_o}\left(\frac{A_{10}}{A_o} - 1\right) \tag{15}$$

2. Specific impulse

$$I_{sp} = \frac{F_s}{f \times g} \tag{16}$$

Table 1: Constants and assumed values

$C_{pc}(J/kgK)$	R (J/kgK)	V_{fx}/V_3 , V_f/V_3	$C_f * A_w/A_3$	η_c, η_b, η_e	γ_c	γ_b, γ_e	T^o
1090	289.3	0.5	0.1	0.9	1.36	1.238	222 K

2.2.1 Variables

The variables used in this optimization problem are as follows

1. $0.3 < q$ (bar) < 0.9. (dynamic pressure limit for hypersonic cruise vehicles) [7]
2. $1.5 < M_3 < 0.5M_0$ (combustor inlet Mach number range)
3. $1 < P_{10}/P_o < 6$ (expansion ratio required to satisfy the geometric constraint)

2.2.2 Constraints

The constraints for this optimization problem are as follows

1. 0.5 bar $< P_3 <$ 1 bar. (The minimum pressure required for combustion to take place and maximum pressure limit for thermal management)
2. $A_{10}/A_0 < 1.5$ (Geometric constraint)
3. $M_4 > 1.2$. (Flow is supersonic throughout)

2.3 Nature Inspired Techniques

In this section the following nature inspired optimization techniques are discussed elaborately. In this work two oldest and most generalized optimization techniques were used namely GA and PSO. In addition we use three new techniques namely TLBO, Harmonic Search and BAT algorithm. These methods are discussed below:

2.3.1 Genetic Algorithm

Genetic Algorithm is one of the oldest and most successful optimization technique based on Nature of evolution [9]. It was originally proposed by John Holland in the 1960's at the University of Michigan, to study the process of evolution and adaption occurring in nature. Genetic Algorithm is inspired by Charles Darwin theory of evolution and natural selection. This uses survival of the fittest approach for selecting the best (fittest) solution from the available solutions.

GA uses three operations to maintain population that evolve from one generation to another. The first operation is "Selection" operation which is inspired by the principle of 'Survival of the Fittest'. The search begins from a randomly generated population that evolve over successive generations (iterations). A fitness function is used to evaluate the performance of the solutions. Each time two solutions are chosen as parent solutions by selection process based on fitness function. The second operation is the "crossover" operation, which is inspired by mating in biological populations. The crossover operator inherits features of good surviving designs from the parent population into the future population, which will have better fitness value on average. The third operation is "mutation" which causes diversity in population characteristics. It causes local modifications to the new generation randomly. The new generation is identical to the parent except one or more changes made by mutation process. Repeat selection, crossover and mutation operations to produce more new solution until the population size of the new generation is the same as that of the old one. The iteration then starts from the new population. Since better solutions have a larger probability to be selected for crossover and the new solution produced carry the features of their parents, it is hoped that the new generation will be better than the old one. The procedure continues until the number of generations is reached to n or termination criteria is met .

2.3.2 Particle Swarm Optimization Algorithm

PSO was developed by James Kennedy and Russell Eberhart in 1995 after being inspired by the study of bird flocking behaviour by biologist Frank Heppner [10]. It is related to evolution-inspired problem solving techniques such as genetic algorithms. PSO simulates the behaviours of bird flocking. Consider the following scenario: a group of birds are randomly searching food in an area. There is only one piece of food in the area being searched. All the birds do not know where the food is. So what's the best strategy to find the food? The effective one is to follow the bird which is nearest to the food.

PSO uses this scenario to solve the optimization problems. In PSO, each single solution is a "bird" in the search space. We call it "particle". All of particles have fitness values which are evaluated by the fitness function to be optimized, and have velocities which direct the flying of the particles. The particles fly through the problem space by following the current particles. PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called pbest. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called gbest. When a particle takes part of the population as its topological neighbours, the best value is a local best and is called lbest.

After finding the two best values, the particle updates its velocity and positions with following equation (17) and (18).

$$v[] = v[] + c1 * rand() * (pbest[] - present[]) + c2 * rand() * (gbest[] - present[]) \quad (17)$$

$$present[] = present[] + v[] \quad (18)$$

where, v[] is the particle velocity, present[] is the current particle (solution). pbest[] and gbest[] are defined as stated before. rand () is a random number between (0,1). c1, c2 are learning factors. Usually c1=c2=2.

2.3.3 Teaching Learning Based Optimization Algorithm

Population based algorithms which are mainly nature inspired and which simulates different natural phenomena to solve a wide range of problems are popular in research fields. Many researchers had proposed a number of algorithms in the past considering different natural phenomena. TLBO is a teaching- learning process-inspired algorithm proposed by Rao et.al based on the influence of a teacher on the output of learners in a class [11]. The algorithm describes the teaching-learning ability of the teacher and learners in a classroom.

In this optimization algorithm a group of learners is considered as population and different subjects offered to the learners are considered as different variables of the optimization problem and a learner's result is analogous to the 'fitness' value of the optimization problem. The best solution in the entire population is considered as teacher. The variables are actually the parameters involved in the objective function of the given optimization problem and best solution is the best value of the objective function. This algorithm is divided in two basic modes of the learning.

- Through teacher (known as the teacher phase)
- Interacting with the other learners(known as the learner phase)

Teacher phase

In this phase the teacher increases the mean result of the class in subjects taught in the class depending on his or her capability. At any iteration i, assume that there are m number of subjects (i.e., Variables), n number of learners (i.e., population size, k=1,2,...n) and $M_{j,i}$ be the mean result of the learners in a particular subject j (j=1,2,...,m) The best overall result $\mathrm{X_{total\text{-}kbest,i}}$ considering all the subjects together obtained in the entire population of learners can be considered as the result of best learner kbest. However, as a teacher is generally considered as highly learned person who shares his or her knowledge with learners. The quality of a teacher affects the outcome of learners. It is therefore apparent that a good teacher trains learners such that they can have better results in terms of their marks or grade. The best learner identified, is considered by the algorithm as the teacher. The difference between the existing mean result of each subject and the corresponding result of the teacher for each subject is given by,

$$Difference\_Mean_{\mathrm{j,k,i}} = r_{\mathrm{i}}(X_{\mathrm{j,kbest,i}} - T_{\mathrm{F}} M_{\mathrm{j,i}}) \quad (19)$$

where $\mathrm{X_{j,kbest,i}}$ is the result of the best learner(i.e. teacher) in subject j. $\mathrm{T_F}$ is the teaching factor which decides the value of mean to be changed, and $\mathrm{r_i}$ is the random number in the range [0, 1]. Value of $\mathrm{T_F}$ can be either 1 or 2 and is decided randomly with equal probability as:

$$T_{\mathrm{F}} = round[1 + rand(0,1)\{2 - 1\}] \quad (20)$$

Based on the $\mathrm{Difference\_Mean_{j,k,i}}$ the existing solution is updated in the teacher phase according to the following expression:

$$X'_{\mathrm{j,k,i}} = X_{\mathrm{j,k,i}} + Difference\_Mean_{\mathrm{j,k,i}} \quad (21)$$

where $\mathrm{X'_{j,k,i}}$ is the updated value of $\mathrm{X_{j,k,i}}$. Accept $\mathrm{X'_{j,k,I}}$ if it gives better function value. All the accepted function values at the end of the teacher phase are maintained and these values become the input to the learner phase. The learner phase depends upon the teacher phase as explained in next step.

Learner phase

In this phase the interaction of learners with one another takes place .the process of mutual interaction tends to increase the knowledge of the learner. The random interaction among learners improves his or her knowledge. Considering a population size of n, the learning phenomenon of this phase expressed below. Randomly select two learners P and Q such that $X_{\text{total-P,i}} \neq X_{\text{total-Q,i}}$ (where $X_{\text{total-P,i}}$ and $X_{\text{total-Q,i}}$ are the updated values of $X_{\text{total-P,i}}$ and $X_{\text{total-Q,i}}$ respectively at the end of teacher phase)

$$X''_{\text{j,P,i}} = X'_{\text{j,P,i}} + r_{\text{i}}(X'_{\text{j,p,i}} - X'_{\text{j,Q,i}}), if X_{\text{total-P,i}} < X_{\text{total-Q,i}} \tag{22}$$

$$X''_{\text{j,P,i}} = X'_{\text{j,P,i}} + r_{\text{i}}(X'_{\text{j,Q,i}} - X'_{\text{j,P,i}}), if X'_{\text{total-Q,i}} < X_{\text{total-P,i}} \tag{23}$$

Accept $X''_{\text{j,P,i}}$ if it gives a better function value.

2.3.4 Harmony Search Algorithm

Harmony Search (HS) is a relatively new population based metaheuristic optimization technique proposed by Geem.et.al [12].HS mimics the musical process of searching for a perfect state of harmony, determined by an aesthetic standard, and has been used to solve optimization problems. In music improvisation process, musician plays different notes of different musical instrument and find the best combination of frequency for best tune, similarly in HS method also best combination of available solutions is selected and objective function is optimized.

The HS algorithm initializes the Harmony Memory (HM) with randomly generated solutions. The number of solutions stored in the HM is defined by the Harmony Memory Size (HMS). Then iteratively a new solution created as follows. Each decision variable is generated either on memory consideration and a possible additional modification, or on random selection. The parameters that are used in the generation process of a new solution are called Harmony Memory considering rate (HMCR) and Pitch Adjusting Rate (PAR). Each decision variable inherits one of the solutions in the HM with probability of HMCR, and an additional modification of this value is performed with a probability of PAR. Otherwise (with probability of 1-HMCR), the decision variable is set to a random value. After new solution is created, it should be updated. In updation process, if new solution is better than the worst solution, then it replaces it in HM. This process is repeated, until a termination criterion is fulfilled.

2.3.5 Bat Algorithm

Bat algorithm has been developed by xin-she yang in 2010 [13]. Bats are fascinating animals as they are the only mammals with wings and they also have advanced capability of echolocation. Micro bats use a type of sonar, called, echolocation, to detect prey, avoid obstacles and their roosting crevices in the dark. These bats emit a very loud sound pulse and listen for the echo that bounces back from the surrounding objects. Their pulses vary in properties and can be correlated with their hunting strategies depending on the species. If we idealize some of the echolocation characteristics of micro bats, a bat algorithm can be developed (5). For simplicity, use the following approximate or idealized rules:

1. All bats use echolocation to sense distance, and they also 'know' the difference between food/prey and background barriers in some magical way.
2. Bats fly randomly with velocity v_i at position x_i with frequency f_{min}, varying wavelength λ and loudness A_0 to search for prey. They can automatically adjust the wavelength (or frequency) of their emitted pulses and adjust the rate of pulse emission r ϵ [0,1],depending on the proximity of their target.
3. Although the loudness can vary in many ways, we assume that the loudness varies from a large (positive) A_0 to a minimum constant value A_{min}.

Another obvious simplification is that no tray tracing is used in estimating the time delay and three dimensional topography. In addition to these simplified assumptions, we also use the following approximation, for simplicity. In general the frequency f in range[f_{min},f_{max}] corresponds to arrange of wavelengths [λ_{min},λ_{max}]. For the bats simulations, we have to define the rule show their positions x_i and velocities v_i in a d- dimensional search space are updated. The new solutions $x^t{}_i$ and velocities $v^t{}_i$ at time step t are given by

$$f_{\text{i}} = f_{\text{min}} + (f_{\text{max}} - f_{\text{min}})\beta \tag{24}$$

$$v_i{}^t = v_i{}^{t-1} + (X_i{}^t - X_0)f_i \tag{25}$$

where β ϵ [0,1] is random vector drawn from a uniform distribution. Here X_0 is the current global best location (solution), which is located after comparing all the solutions among all the n bats. As the product $\lambda_i f_i$ is the velocity increment, we can use either f_i(or λ_i) to adjust the velocity change while fixing the other factor λ_i(or f_i), depending on the type of the problem of interest. For the local search part, once a solution is selected among the current best solutions, a new solutions for each bat is generated locally using random walk

$$X_{\text{new}} = X_{\text{old}} + \epsilon A_t \tag{26}$$

where $\epsilon\epsilon$ [-1,1] is a random number, while $A^t = < A_i{}^t >$ is the average loudness of all the bats at this time step.

3 RESULTS AND DISCUSSION

An in house developed MATLAB code has been developed to solve the mathematical stream thrust model using nature inspired techniques. An integrated stream thrust module is developed which consisted sub modules of compression combustion and expansion systems. The ambient conditions are calculated using a module where freestream dynamic pressure and Mach number are input parameters which is based on 1976 standard atmosphere model. Input parameters for the stream thrust model are freestream Mach number, dynamic pressure and combustor inlet Mach number. The stream thrust module has been tested using available literature [8].

Comparison of various nature inspired techniques for freestream Mach number of 8 is carried out (Table2). From Table 2, we can observe that all the nature inspired techniques predict same optimum value for the given Mach number. All the evolutionary and swarm intelligence based algorithms are probabilistic algorithms and require common controlling parameters like population size, number of generations elite size etc. In addition to common control parameters different algorithms requires its own algorithms specific control parameter. For example GA uses mutation rate, crossover rate, similarly PSO uses inertia weight, social & cognitive parameters. The performance of above-mentioned algorithms is greatly influenced by their respective algorithm-specific parameters in addition to the common control parameters such as population size and number of generations. Selection of suitable values of these algorithm-specific parameters for a particular application in itself is a complex problem. Teaching-learning- based optimization (TLBO) requires only common controlling parameters like population size and number of generations for its working making it more user friendly. In this way TLBO can be said as an algorithm-specific parameter-less algorithm. Hence TLBO is recommended for optimization of single objective optimization problems. Variation of optimized specific impulse with freestream Mach number is studied using TLBO and GA (Table3 and 4). Salient characteristic inferences from results are:

- Specific impulse is maximum for lower dynamic pressure i.e higher altitudes and lower combustor inlet Mach numbers for a given freestream Mach number.
- Specific impulse decreases with increase in freestream Mach number.
- The amount of underexpansion required to maintain constant exit to inlet ratio increases with increase in freestream Mach number

Method	q (bar)	M_3	$\frac{P_{10}}{P_o}$	T_3(K)	$\frac{A_3}{A_0}$	M_4	T_4(K)	$\frac{A_4}{A_3}$	M_{10}	T_{10}(K)	$\frac{A_{10}}{A_0}$	I_{sp}(s)
GA	0.3	2.79	4.41	1222.4	0.0484	1.83	2594.6	2.46	3.51	1473.1	1.5	700.65
PSO	0.3	2.79	4.41	1222.4	0.0484	1.83	2594.6	2.46	3.51	1473.1	1.5	700.65
TLBO	0.3	2.79	4.41	1222.4	0.0484	1.83	2594.6	2.46	3.51	1473.1	1.5	700.65
HS	0.3	2.79	4.41	1222.4	0.0484	1.83	2594.6	2.46	3.51	1473.1	1.5	700.65
BAT	0.3	2.79	4.41	1222.4	0.0484	1.83	2594.6	2.46	3.51	1473.1	1.5	700.65

Table 2: Comparison of various nature inspired techniques for freestream Mach number of 8

M0	q(bar)	M_3	$\frac{P_{10}}{P_o}$	T_3(K)	$\frac{A_3}{A_0}$	M_4	T_4(K)	$\frac{A_4}{A_3}$	M_{10}	T_{10}(K)	$\frac{A_{10}}{A_0}$	I_{sp}(s)
8.0	0.3	2.79	4.41	1222.40	0.04840	1.83	2594.60	2.46	3.51	1473.10	1.5	700.65
7.5	0.3	2.64	4.25	1146.30	0.05310	1.71	2495.51	2.52	3.36	1437.38	1.5	745.55
7.0	0.3	2.48	4.09	1071.37	0.05890	1.58	2399.91	2.59	3.20	1404.24	1.5	793.78
6.5	0.3	2.30	3.95	1004.52	0.06610	1.45	2315.10	2.67	3.04	1379.31	1.5	840.86
6.0	0.3	2.12	3.81	939.09	0.07525	1.31	2233.87	2.75	2.88	1357.69	1.5	890.64
5.5	0.3	1.93	3.67	873.95	0.08727	1.17	2155.07	2.85	2.71	1338.91	1.5	943.84

Table 3: Variation of optimized specific impulse with freestream Mach number using TLBO

M0	q(bar)	M_3	$\frac{P_{10}}{P_o}$	T_3(K)	$\frac{A_3}{A_0}$	M_4	T_4(K)	$\frac{A_4}{A_3}$	M_{10}	T_{10}(K)	$\frac{A_{10}}{A_0}$	I_{sp}(s)
8.0	0.3	2.79	4.41	1222.40	0.04840	1.83	2594.60	2.46	3.51	1473.10	1.5	700.65
7.5	0.3	2.64	4.25	1146.30	0.05310	1.71	2495.51	2.52	3.36	1437.38	1.5	745.55
7.0	0.3	2.48	4.09	1071.37	0.05890	1.58	2399.91	2.59	3.20	1404.24	1.5	793.78
6.5	0.3	2.30	3.95	1004.52	0.06610	1.45	2315.10	2.67	3.04	1379.31	1.5	840.86
6.0	0.3	2.12	3.81	939.09	0.07525	1.31	2233.87	2.75	2.88	1357.69	1.5	890.64
5.5	0.3	1.93	3.67	873.95	0.08727	1.17	2155.07	2.85	2.71	1338.91	1.5	943.84

Table 4: Variation of optimized specific impulse with freestream Mach number using GA

4 CONCLUSION

Optimization of specific impulse of scramjet engine has been carried out using stream thrust analysis by nature inspired techniques. Various nature inspired techniques such as GA, PSO, HS, TLBO and BAT algorithms are used to optimize the specific impulse. All the evolutionary algorithms predicts the same optimum value. All the algorithms except TLBO require their algorithm specific control parameters in addition to population size and number of generations. Hence, TLBO can be said as an algorithm-specific parameter-less algorithm and is recommended for single objective optimization problems. The results of the constrained based optimization show that specific impulse is maximum at lower dynamic pressures (higher altitude) and lower combustor inlet Mach number for a given freestream Mach number irrespective of the algorithm used which implies flying at higher altitudes will provide a better performance of the engine.

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