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Comparing Two and Three Dimensional Optimization of Turbojet Engine with Multi Target Genetic Algorithm

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Abstract- In this paper, turbojet engine in ideal condition will be optimized by multi target genetic algorithm. The target functions are specific thrust (ST), specific fuel consumption (SFC) and thermal efficiency (ηt) that once will simultaneously be optimized by two by two way and the results will be revealed in the Pareto curves. For the second time these three objective functions will be optimized at the same time. At the end the findings of two by two ways will be compared with the results of three objective functions.

Design variables are considered as Mach number and total compressor pressure ratio. The significant relation between objective functions is introduced according to Pareto points. There is no doubt that these functions without using methods are not considerable.

Keywords- *Genetic Algorithm, Pareto, Multi target optimization, Crossover, Mutation, Turbojet engine*

I. INTRODUCTION

As a matter of fact optimization procedure is defined as a way to find numerical collection for design vector variables. These are various numerical methods included Gradient methods to find optimum points. However some basic problems such as their great dependency to first assumptions can move the problem toward local optimization than absolute optimization. On the other hand in non continues or non derivative functions by using gradient methods seems improbable so other optimization methods especially genetic algorithm can solve this problem [3], [4].

These evolutionary algorithms are inspired by nature and their main deference with old ones is that in these methods, we do optimization by function not by their gradients.

Some of the recent evolutionary approaches to multi objective optimization are non-dominated sorting genetic algorithm (NSGA-II), strength Pareto evolutionary algorithm (SPEA), Pareto archived evolution strategy (PAES), multi objective differential evolution (MODE) and others. Among these SPEA [11,12] have been applied to multi objective ORPD problem and MODE [13] has been applied to multi objective optimal power flow problem. Though NSGA-II [14] algorithm encompasses advanced concepts like elitism, fast non-dominated sorting approach and diversity maintenance along the Pareto-optimal front, it still falls short in maintaining lateral diversity and obtaining Pareto-front with high uniformity. To overcome this shortcoming, [15] proposed a technique called controlled elitism which can maintain the diversity of non-dominated front laterally. Also to obtain Pareto-front with high uniformity, DCD based diversity maintenance strategy is proposed recently [16].

In multi target optimization, several targets will be optimized simultaneously. These targets may be in disagreement with each other, thus optimum of a target may deteriorate that of another target. Pareto was an Italian economist that revealed the context of multi target optimization [5]. Pareto points do not have any superiority toward each other but comparing to other points, they are superior in research. NSGA method was suggested by Deb [6] and SPEA method was introduced by Zitzler and Thiele [7].

In this study, design variables such as inlet Mach number and total compressor pressure ratio are considered. Selective multi target in ideal subsonic turbo jet included specific thrust, specific fuel consumption and thermal efficiency and with considering design variables will be optimized two by two. The results will be revealed by Pareto curves. Our goal is decreasing fuel consumption and increasing thrust and thermal efficiency. Can we find a design vector that is minimum in fuel consumption and maximum in thrust and thermal efficiency?

II. TURBO JET THERMODYNAMIC MODEL

Operating fuel in turbo jet engine is air which by changing in kinetic energy in inlet comparing with outlet can create thrust.

Ideal turbojet engine equations are shown in table A [8]. Inlet parameters in this cycle included flight Mach number (M_0), inlet air temperature (T_0, K), temperature coefficient(γ), heating value (hpr, kj.kg-1), burner exit total temperature (Tt_4,K), total compressor pressure ratio (π_c).

Outlet parameters involves specific thrust (ST, N.kg-1.S-1), fuel/air ratio (f), thrust specific fuel consumption (TSFC, kg.S-1.N-1) and thermal efficiency (ηt).

In this paper hpr=48000 kj.kg-1, γ=1.4, Tt4=1666K, T0=216.6K. Flight Mach number 0<M0≤1 and total compressor pressure ratio 1≤π≤40 are considered as design variables [8].

III. MULTI TARGET GENETIC ALGORITHM

A. Multi target optimization

In multi target optimization problems, we are looking for vector design $X^*=[x^*_1, x^*_2, \ldots, x_n^*]^T$ which is member of R_n that target functions are

$$F=[f_1(X), f_2(X), f_3(X)]^T \quad (1)$$

Member of Rk according to m number condition

$$g_i(X) \leq 0 \;,\; i=1,2,\ldots,m \quad (2)$$

And p number of equal condition

$$h_j(X)=0 \;,\; j=1,2,\ldots,p \quad (3)$$

will optimize [9], [10].

B. Defining Predominant Pareto

The vector U=[u1, u2,…, u_k]ε R_k is predominant to vector V if and if

$$\forall i \in \{1,2,\ldots,k\}, u_i \leq v_i \wedge \exists j \in \{1,2,\ldots,k\} : u_j < v_j \quad (4)$$

C. Defining optimum Pareto

A point like X*ε Ω (Ω is an accepted design region which satisfy 2, 3 equations) is called optimum Pareto if and only if F(X*)<F(X) or on the other hand

$$\forall i \in \{1,2,\ldots,k\}, \forall X \in \Omega - \{X^*\} \quad f_1(X^*) \leq f_1(X) \quad (5)$$
$$\wedge \exists j \in \{1,2,\ldots,k\} : f_j(X^*) < f_j(X)$$

D. Defining Pareto collection

In multi target optimization problems, a Pareto collection (Θ*) included all design vectors of optimum Pareto. On the other hand

$$\Theta^* = \{X \in \Omega \mid \exists X' \in \Omega : F(X') \prec F(X)\} \quad (6)$$

E. Defining Pareto Front

Vectors including target functions which are made from vectors of Pareto collections (Θ*) are called Pareto Front.

The results of multi target optimization have no superiority toward each other and are called non superior results.

In figure (1) for example can see the Pareto points, in this figure by moving from A to B (or vise versus), any improvement in condition of any target functions can deteriorate the condition of at least one target function of problem, (the goal is to minimize or maximize both target functions).

Pareto optimum points almost are located in boundary lines of design region or are over lapped points of target functions.

In figure (1) the bold line shows such boundary line of two target functions which its component points are called Pareto Front.

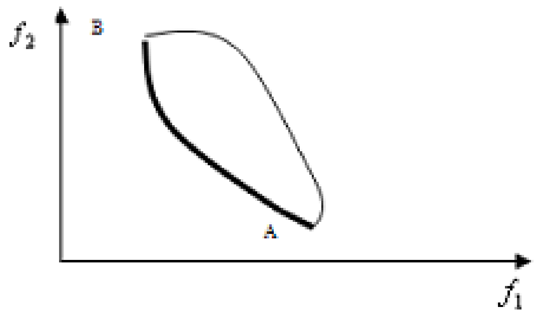

Fig. 1 Pareto points in a curve form

F. Multi target genetic algorithm (NSGAII)

First stage of this method, N is the primary population which is generated randomly (R_t). Then these populations will be categorized and vectors which satisfy the condition of equation (4) will be categorized in lower levels, then among these populations, some populations will be selected randomly for crossover and mutation. The population which is created by crossover and mutation (Q_t) will be added to primary population and again the total population will be classified.

The base of NSGAII is that while reproduction is continuing, the number of population must be constant, so the population in higher levels will be eliminated.

The end of a reproduction is an improved population. Diagram (a) shows a reproduction in NSGAII.

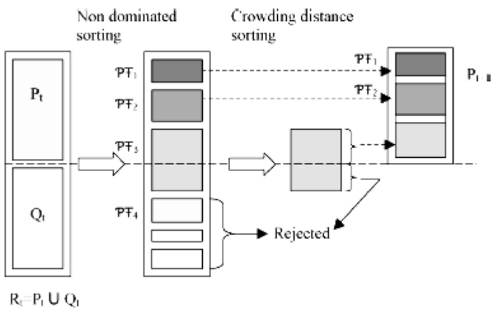

Fig a. reproduction procedures

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IV. MULTY TARGET OPTIMIZATION OF TURBO JET ENGINE WITH MULTI TARGET GENETIC ALGORITHM TWO BY TWO WAY

A. Optimization according to thermal efficiency and specific fuel consumption target functions (η_t, SFC)

Figure (2) is the collection of points resulting from optimization according to two target functions SFC and η_t which is generated by NSGAII. In this figure five optional design vectors are shown. By comparing design vectors 2 and 4, we can show that by increasing 16.1% in SFC, thermal efficiency will be increased 29.8%.

Why multi target optimization is superior to single target optimization? In optimization which was according to η_t and SFC, we see that increasing thermal efficiency can lead to increasing fuel consumption, since the target is increasing η_t and decreasing SFC, if we do single target optimization, the results will be points one and five. While the point one has the minimum SFC and thermal efficiency and point five has the maximum SFC and thermal efficiency. It should be mentioned that point one is according to single target optimization of SFC and point five is according to single target optimization of η_t.

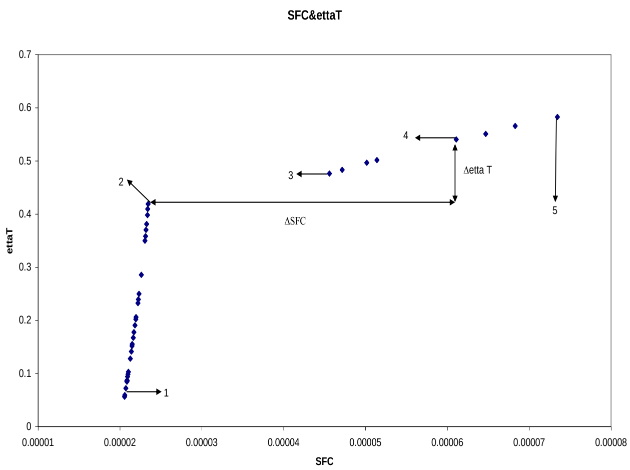

Fig. 2 Pareto points of thermal efficiency and fuel consumption

B. Optimization according to specific thrust and thermal efficiency target functions (ST,η_t)

Figure (3) shows the Pareto points according to ST and η_t.

By comparing design vectors two and three, we consider that with increasing 11.9% in specific thrust, thermal efficiency will decrease 36.2%. So in design viewpoint, point two is more valuable than point three. Design vector one amount all design vectors has the least ST and the most η_t, while design vector seven has the most ST and the least η_t.

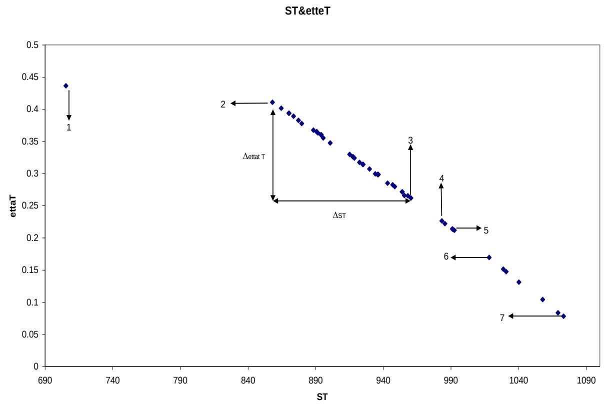

Fig. 3 Pareto points of thrust and thermal efficiency

C. OPTIMIZATION ACCORDING TO SPECIFIC THRUST AND SPECIFIC FUEL CONSUMPTION TARGET FUNCTIONS (ST,SFC)

Figure (4) shows the Pareto points according these two target functions that obtained from multi genetic algorithm. Considering this figure, we understand that increasing ST will happen with increasing SFC. On the other hand optimization a target function can cause to deteriorate another one.

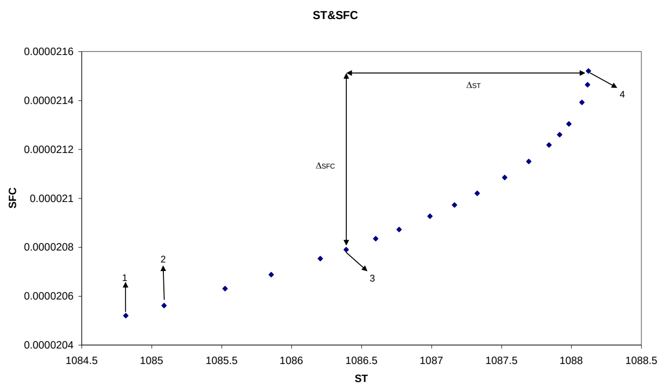

Fig. 4 Pareto points of thrust and fuel consumption

V. OPTIMIZATION ACCORDING TO THREE TARGET FUNCTIONS (ST, SFC, η_T)

Pareto points are shown two by two ways. It's obvious that these design vectors which are product of optimization are representative of 3D curve that are showed two by two ways.

Similar points to one number are shown in figures (5), (6) and (7).

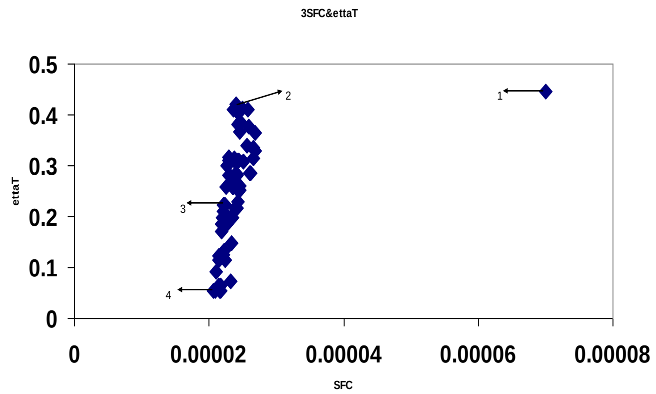

Fig. 5 Pareto points of thermal efficiency and fuel consumption according to three target functions

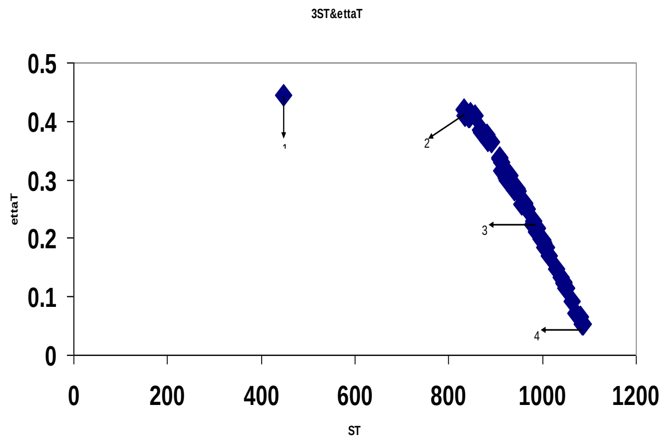

Fig. 6 Pareto points of thermal efficiency and thrust according to three target functions

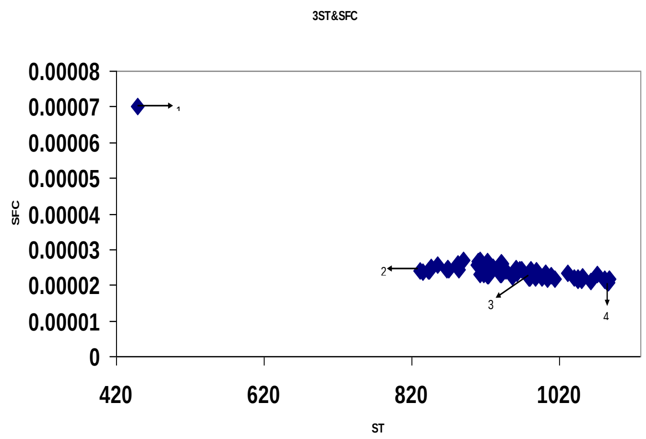

Fig. 7 Pareto points of thrust and fuel consumption according to three target functions

Comparing two and three design vectors, it can be inferred that by 18% increasing ST, SFC will decreased to 8% but thermal efficiency will fall to 47%. By comparing one and two design vectors, we conclude that increasing 85% in ST will be accompanied with loss of 5.6% in thermal efficiency and fall of 66% in SFC.

VI. Comparing Optimization with Two and Three Objective Function

As it was revealed Pareto points include a set of points that don't have any superiority to each other or on the other hand, it is possible that in this set movement from one point to another causes improvement in an objective function, but in another function we may not see such event. It is obvious that by increasing number of objective function, the more expansion will be found in Pareto point since it is possible that the design vector is considered bad from some objective functions but is ok from another objective functions or even just from an objective function. Perspective, this expansion is dependent on the number of objective functions.

For the better comparing optimization between two and three objective functions, figures (8), (9), (10) of two objective functions are revealed with three objective functions.

As it shown in optimization with three objective functions, the expansion of the responds is much more than that of two objective functions.

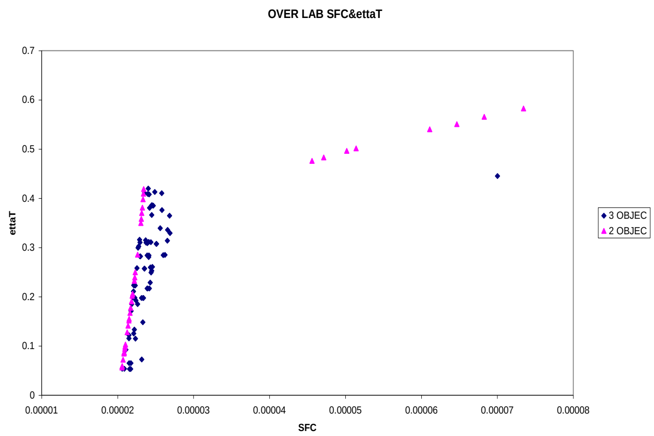

Fig. 8 Thermal efficiency and specific fuel consumption in two and three objective optimization

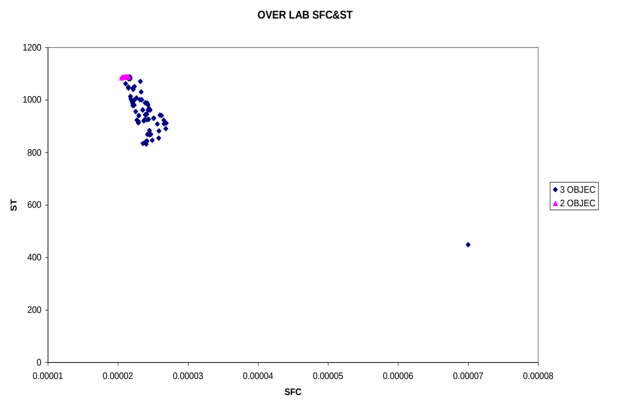

Fig. 9 Specific thrust and specific fuel consumption in two and three objective optimization

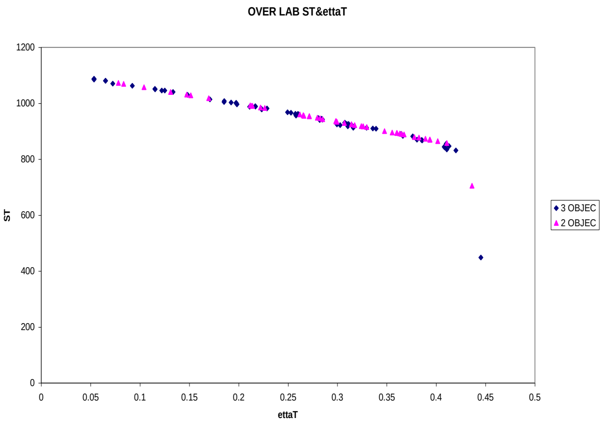

Fig. 10 Specific thrust and thermal efficiency in two and three objective optimization

VII. CONCLUSION

Several functions may optimize simultaneously in optimization. Now if we consider optimization problem as a single target, we can not see the results of the other functions in optimum vector. So the optimum point of a target function may be the weak point of others.

In high pressure coefficient $30<\pi_c\leq 40$ and $0<M_0\leq 0.98$, specific thrust and fuel consumption will be improved but in this range, we can't expect that thermal efficiency be more than 42%.

Around $M_0=1$ and in low pressure coefficient ($1\leq\pi_c<2.1$), we can reach to the highest thermal efficiency (60%), however in this range fuel consumption will be in its worst condition ($4.55897\leq SFC\times 105\leq 7.3457$).

It obtained from Pareto points that fuel consumption is effected by pressure coefficient than Mach number (Table 1).

According to Pareto figures which are shown in this paper, we can conclude that SFC is almost proportional with square of ST (SFC α ST^2) and thermal efficiency is proportional with ST (η_t α ST). Other important results are summarized two by two in table (1).

TABLE 1
The results of two by two target function optimization

η_t, ST	
$0<\eta_t<0.44$ $705\leq ST\leq 1074$	
M_0	$0.1<M_0\leq 1$
π_c	$2.5<\pi_c<34$

SFC,ST	
$2.05\leq SFC\times 10^5<2.2$ $1084<ST<1089$	
M_0	$M_0=0.1$
π_c	$30<\pi_c\leq 40$

η_t, SFC	
$0<\eta_t<0.42$ $2.06<SFC\times 10^5<2.34$	$0.47<\eta_t<0.6$ $4.56\leq SFC\times 10^5\leq 7.34$
$0<M_0\leq 0.98$ $\pi_c=40$	$M_0\cong 1$ $1\leq\pi_c<2.1$

Finding results included specific boundaries for target functions and design variables. For example if optimization is according to η_t, SFC: if $0<\eta_t<0.42$, fuel consumption must be to [2.056e-5, 2.344e-5] and flight Mach number must be [0, 0.98] and total compressor pressure ratio must be 40.

INDEX

a_0 Velocity of sound at inlet…………………..m/s
$\dot{m}_0$ Mass flow rate…………………………..….kg/s
T_{t4} Burner exit total temperature………………K
T_0 Inlet temperature……………………………K
h_{pr} Heating value ………………………..….kJ/kg
V_0 Air velocity at inlet…………………..…….m/s
g_c Newton's constants………………………...kg-m.
R Gas constants……………………………….J/kg.K
F Thrust……………………………………..……N
M_0 Mach number
τ_r Total static temperature ratio at inlet
τ_t Burner exit/inlet total temperature ratio
τ_λ Burner exit total enthalpy/inlet total enthalpy
τ_c Compressor exit total temperature/Compressor inlet temperature
f Fuel/air ratio
ST Specific thrust
SFC Specific fuel consumption
η_t Thermal efficiency

X^* Vector of optimal design variables

π_c Total compressor pressure ratio

F(X) Vector of objective function

REFERENCES

[1] J.S. Arora, Introduction to Optimum Design, McGraw-Hill, New York, 1989.
[2] S.S Rao, Engineering Optimization: Theory and Practice, Wiley, New York, 1996.
[3] D.E. Goldberg, Genetic-ALgorithems in search, Optimization, and Machine Learning, Addison-Wesley, Reading, MA, 1989.
[4] T.Back, D.B. Fogel, Z. Hand book of Evolutionary Computation, Oxford University press,New York/Oxford, 1997.
[5] V. pareto, Cours d'economic politique, Lausanne, Switzerland, 1896.
[6] N. Srinivas, K. Deb, Multiobjective optimization using nondo- minated sorting in genetic algorithms, Evolutionary Comput.2(3) (1994) 221-248.
[7] C.M. Fonseca, P.J. Fleming, Genetic algorithms for multiobje-ctive optimization: Formulation,discussion,san Mateo, CA, 1993, pp.416-423.
[8] Jack D. Mattingly, Elements of Gas Turbine Propulsion, McG-raw-Hill series in mechanical engineering, 1996.
[9] Pareto, coursd's economic politique, Rouge, Lausanne, Switzerland, 1896
[10] A.Oseyezka, Multicriteria optimization for engineering design, in:J.S Gero(Ed.), Design optimization, Acadamic press, New York, 1985, pp 193-227.
[11] Abido MA, Bakhashwain JM. Optimal VAr dispatch using a Multi objective evolutionary algorithm. Int J Electr Power Energy Syst 2005;27(1):13–20.
[12] Sailaja kumari M, Maheswarapu S. Enhanced genetic algorithm based computation technique for multi-objective optimal power flow solution. Int JElectr Power Energy Syst 2010;32(6):736–42.
[13] Varadarajan M, Swarup KS. Solving multi-objective optimal power flow using differential evolution. IEE Proc Gener Transm Distrib 2008;2(5):720–30.
[14] Deb K, Pratap A, Agarwal S, Meyarivan T. A fast elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans Evol Comput 2002;6(2):182–97.
[15] Deb K. Multiobjective optimization using evolutionary algorithms. Chichester (UK): Wiley; 2001.
[16] Luo B, Zheng J, Xie J, Wu J. Dynamic crowding distance – a new diversity maintenance strategy for MOEAs. In: Proceedings of the IEEE international conference on natural computation; October 2008. p. 580–5.

TABLE 1
TURBOJET EQUATION [8]

$$R = \frac{\gamma - 1}{\gamma} C_P$$

$$a_0 = \sqrt{\gamma R g_c T_0}$$

$$\tau_r = 1 + \frac{\gamma - 1}{2} M_0^2$$

$$\tau_\lambda = \frac{T_{t4}}{T_0}$$

$$\tau_c = (\pi_c)^{(\gamma - 1)/\gamma}$$

$$\tau_t = 1 - \frac{\tau_r}{\tau_\lambda}(\tau_c - 1)$$

$$\frac{V_9}{a_0} = \sqrt{\frac{2}{\gamma - 1}\frac{\tau_\lambda}{\tau_r \tau_c}(\tau_r \tau_c \tau_t - 1)}$$

$$ST = \frac{F}{\dot{m}_0} = \frac{a_0}{g_c}\left(\frac{V_9}{a_0} - M_0\right)$$

$$f = \frac{C_p T_0}{h_{pr}}(\tau_\lambda - \tau_r \tau_c)$$

$$SFC = \frac{f}{ST}$$

$$\eta_t = 1 - \frac{1}{\tau_r \tau_c}$$

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