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Optimal Thermodynamic Design of Turbofan Engines using Multi-objective Genetic Algorithm

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ABSTRACT

The aim of this study is to optimize the performance functions of turbofan engines. In this way, the multi-objective genetic algorithm is employed to optimal design of turbofan with considering the off-design model of engine. The design variables are high-pressure compressor pressure ratio, low-pressure compressor pressure ratio, fan pressure ratio and bypass ratio. They are calculated in such a way that the performance functions are at their best conditions simultaneously. The performance functions are specific thrust at take-off, and thrust specific fuel consumption, propulsive, thermal, and overall efficiencies at cruise. The optimization is carried out using the modified NSGA II which is among the best multi-objective genetic algorithm methods. The results of this optimization will be a set of vectors which the designer may choose one of those according to the problem conditions.

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NOMENCLATURE

a_0	Velocity of sound at inlet (m/s)	π	Pressure ratio
C_P	Specific heat at constant pressure (kJ/kg K)	τ	Temperature ratio
F	Thrust (N)	π_f	Density (kg/m^3)
$\dot{m}_0$	Mass flow rate (kg/s)	τ	Fan pressure ratio
$\dot{m}_f$	Mass fuel rate (kg/s)	α	Bypass ratio
M_0	Flight Mach number	e	Polytropic efficiency
h	Flight altitude (Km)	η_{mH}	High pressure spool mechanical efficiency
h_{PR}	Heating value (kJ/kg)	η_{mL}	Low pressure spool mechanical efficiency
R	Gas constant (J/kg/s)	**Subscripts**	
$F/\dot{m}_0$	Specific thrust (N/kg/s)	cH	High pressure compressor
S	Thrust specific fuel consumption (mg/s)/N	cL	Low pressure compressor
T_{t4}	Turbine inlet temperature (K)	tH	High pressure turbine
T	Temperature (K)	tL	Low pressure turbine
V	Velocity (m/s)	f	Fan
γ	Ratio of specific heats	b	Burner
η_T	Thermal efficiency	n	Nozzle
η_P	Propulsive efficiency	fn	Fan nozzle
η_o	Overall efficiency	d	Diffuser

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1. INTRODUCTION

Optimization is playing the main role in many engineering problems. Principally, optimization process is defined to find a set of values for a vector of design variables which yields an optimal value for an objective function. In such single-objective optimization problems, constraining functions may or may not exist. Therefore, they are commonly known as constrained or unconstrained optimization problems, respectively. There are numerous calculus-based methods including gradient approaches which search for local optimal solutions. These methods are well documented in [1, 2]. Due to some inherent difficulties of gradient approaches such as their heavy dependence on initial guesses, a local optimal solution may be found instead of a global one [1]. This led to the use of other heuristic optimization methods especially genetic algorithm which has been widely used during the past decade.

Such algorithms which have been derived from nature [3, 4], are different from other traditional calculus-based methods. The significant difference between these methods is that, unlike the traditional methods, genetic algorithms do not use a single point within the search space. Instead, they use a population of selected solutions. This feature may significantly reduce the risk of being trapped in local optimal solutions [5].

In multi-objective optimization problems, there are number of objective functions which have to be simultaneously optimized. These objectives are usually in conflict with each other. Improving one objective function will lead to decline in another. Therefore, there is no single optimal solution which can be the best according to all the objective functions. Instead, there is a set of optimal solutions known as Pareto optimal solutions which make a significant difference between single-objective and multi-objective optimization problems [6-9].

Vilfredo Pareto was an Italian sociologist and economist who introduced multi-objective optimization in Economics for the first time [10]. A Pareto front within objective functions space in multi-objective optimization refers to a set of solutions which are not dominant to each other, but are of higher order in comparison with the other solutions within the search space. Rosenberg was the first to report the early uses of evolutionary searches in 1960 [11]. Since then, the interest toward using evolutionary algorithms for multi-objective problems has been on the rise. Among these algorithms, VEGA proposed by Schaffer [12], Fonseca and Fleming's Genetic Algorithm (FFGA) [7], Non-Dominated Sorting Genetic Algorithm (NSGA) proposed by Srinivas and Deb, Strength Pareto Evolutionary Algorithm (SPEA) proposed by Zitzler and Thiele [13], and Pareto Archive Evolution Strategy (PAES) proposed by Knowles and Corne [14] are the most significant ones. An excellent comprehensive review of these methods has been presented in [15-17]. In addition, Coello coello has gathered a comprehensive internet-based collection of papers. Basically, both NSGA and FFGA methods are Pareto-based approaches which utilize non-dominated sorting process which was first proposed by Goldberg [3]. The lack of elitism in NSGA algorithm led to the modified version of NSGA-II [18] in which the sharing method has been replaced by a direct elitist method in order to preserve the population convergence. This modified algorithm is the manifestation of the latest developments in multi-objective evolutionary problems[19]. In reference [18], NSGA-II has been compared with SPEA as well as PAES and its superiority and better Pareto distribution has been depicted. Some other studies, included in [20], show that the elitist version of NSGA (NSGA-II) and SPEA are of equal performance. Despite its popularity and effectiveness, NSGA-II suffers the limitation that it can only optimize with two objective functions. In [21], Atashkari et al. modified this algorithm making it capable of optimizing with more than two objective functions while preserving population convergence.

In real-world engineering design, there exist complex optimization problems which are naturally multi-objective. The objectives in these systems are usually in conflict and disagreement. Therefore, Pareto solutions provide a better understanding of conflicting objectives. Toffolo and Lazareto conducted a thermal-economic analysis in which energy and economy were the conflicting objectives in a power plant [22]. A similar approach was considered by Wright et al. in multi-objective optimization of a building thermal design problem [23]. Roosen et al. studied the multi-objective optimization of combined cycle power plant [24]. Oyama and Liou employed multi-objective genetic algorithm in order to optimize the engine pump of a rocket [25]. Their purpose was to yield those design parameters which maximize the pump head and minimize the inlet power. Another application of genetic algorithm in optimization of turbofan engines has been demonstrated by Homaei Fard, Lai, and McCormick [26] in which they studied the design point model of turbofan engines. The considered objective functions include specific thrust, and overall efficiency. First, single-objective optimization is done for each objective functions. Then, the two objective functions are combined and single-objective optimization is once again done for the new function. Optimization is done single-objectively and in multi-objective mode, the two functions got merged by assigned specific weights. Assigning the weights are of crucial importance since they may significantly change the responses. Whereas in multi-objective optimization, guessing or assigning weights is not necessary. Another downfall of this study is that it only considers the design point model. Silva, Fleming et al. also studied a gas turbine engine using genetic algorithm [27]. The purpose of this single-objective optimization is minimizing fuel consumption while maintaining nominal thrust output, maximizing thrust for the same fuel consumption and minimizing turbine blade temperature. To do this, a PI controller is used to control the engine which uses the three variables of the exit nozzle area, fuel flow, and the angle of inlet flow to stabilize the system. The calculations have been done at zero altitude and zero Mach number. The same group designed a non-linear controller for a specific engine using Multi-variable regression, multi-objective genetic algorithm, and experimental data [28]. Atashkari et al. achieved an optimal group of design variables in turbo jet engines including inlet Mach number, compressor pressure ratio, and turbine inlet temperature using Pareto approach in multi-objective optimization [21]. In their study, pairs of conflicting objectives in an ideal subsonic turbojet engine have been chosen to be optimized. These pairs include thermal efficiency and thrust efficiency along with specific fuel consumption and specific thrust. To do this, a so-called ε-elimination algorithm has been suggested to improve the performance of NSGA-II in terms of population convergence and Pareto fronts. This method is generally known as Modified NSGA-II. This algorithm can be used in multi-objective optimization with more than two objective functions. Subsequently, four-objective optimization of turbojet engine considering all the above-mentioned objectives has been done. This paper just used the design point thermodynamic model of an ideal turbojet to find the optimized values of the objective functions. They also modeled the optimized model using neural networks and evolutionary algorithms [29]. Noori et al. investigated a similar study on an ideal turbojet engine with afterburner using Modified NSGA-II [30]. They determined the design parameters of turbojet engine in such a way that the considered objective functions will be at their best performance conditions. The design parameters include turbine inlet temperature, afterburner exit temperature, compressor pressure ratio, and inlet Mach number. The objective functions include thermal efficiency, propulsive efficiency, thrust specific fuel consumption, and specific thrust. First, the optimization has been performed for two by two and then has been done for all the objective functions. In [30], the performance of Modified NSGA-II is compared to other commonly used algorithms.

All the above-mentioned researches, have used the on-design model of turbofan engine. Using the on-design model causes the designer to be limited in a specific Altitude.

In this study with considering the off-design model of turbofan engine, the design parameters are selected in such a way that all of the performance functions simultaneously are at their best conditions. The performance functions are the specific thrust at take-off and thrust specific fuel consumption and propulsive, thermal and overall efficiencies at cruise.

2. THERMODYNAMIC ANALYSIS OF TURBOFAN ENGINE

Thermodynamic analysis of turbofan engine which includes the study of thermodynamic changes in working fluid while passing through engine is divided into two entirely distinct categories: on-design analysis (parametric cycle analysis) and off-design analysis (engine performance analysis). In on-design analysis, the engine geometry is not considered and in the analysis of performance curves, each point represents a different engine. It is often said that the on-design analysis studies a rubber engine [31]. In order to estimate the performance of the engine at different conditions, a model is needed which is capable of describing the behavior of the engine components at conditions other than those of design point. At the late sixties, the on-design optimization was considered sufficient. However, today, mostly due to economic reasons, an off-design model seems to be essential at early design stages [32]. The main objective of all the off-design models is to calculate the working fluid state at different sections of main stream within the engine. Using these results it would be possible to derive thrust, fuel consumption, and all fundamental parameters of engine components. The series of books have considered the off-design study of turbofan engines including Cohen et al. in [33], Oates in [34], Walsh in [35], Mattingly in [36]. Mattingly analysis the performance of the engine by replacing the constant values yielded at engine pressure and temperature ratio function with those of the same function in on-design mode. This study employs the latter analysis to calculate the engine performance in the off-design condition. It also uses a zero-dimensional model, which is of frequent application due to its simplicity and independence from the accurate description of engine geometry [33].

3. ASSUMPTIONS

Figure 1 illustrates a turbofan engine. Turbine and compressor are divided into Low Pressure and High Pressure sections. The High Pressure turbine turns the High Pressure compressor via High Pressure spool. As well, the Low Pressure turbine turns the Low Pressure compressor via Low pressure spool. The mass flow passing through the engine core and fan are $\dot{m}_C$ and $\dot{m}_F$ respectively. The ratio of mass flow through fan to mass flow through engine core is introduced as bypass ratio and is shown by α.

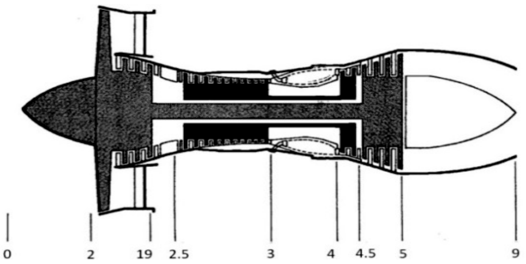

Figure 1. Turbofan engine [39].

The Sea-Level static conditions are considered as the design point conditions for gas turbine variables [31] and [36]. The assumed condition in turbofan engine is the one in which the entrance nozzles at High-Pressure turbine as well as Low-Pressure turbine experience choking. In addition, the nozzle areas are considered constant at these sections. This type of turbines is known as Fixed Area Turbine (FAT). This assumption is valid within a wide performance range of a gas turbine engine [33, 36]. It is assumed that, the turbine cooling and leakage effects are neglected and the turbine power is not used to run the side components. Gas is also considered perfect at both upstream and downstream of combustion chamber.

All the governing equations have been achieved and fully solved in [37] and performance curves of turbofan engine have been thoroughly studied.

4. INPUT AND OUTPUT PARAMETERS AND CONSTRAINTS

Input parameters are assumed to be those variables of independent nature. Applying any change in the value of each input parameter may change all or some objective functions. In fact, all input parameters affect the optimization of objective functions. However, just some input parameters, due to physical, chemical, and ambient limitations, can be considered as design parameters. Among the input parameters, four parameters of high-pressure compressor pressure ratio (π_{cH}), low-pressure compressor pressure ratio (π_{cL}), fan pressure ratio (π_f), and bypass ratio (α) are considered as design variables. The most important output parameters which are considered as objective functions in the turbofan engine are Specific thrust, Thrust specific fuel consumption, propulsive efficiency, thermal efficiency, and overall efficiency. The presented functions in turbofan engine come in the form of Equations (1) to (5) [36]:

$$\frac{F}{\dot{m}_0}=\frac{1}{1+\alpha}a_0\left[(1+f)\frac{V_9}{a_0}-M_0+(1+f)\times\frac{R_t T_9/T_0}{R_c V_9/a_0}\frac{1-P_0/P_9}{\gamma_c}\right]+\frac{\alpha}{1+\alpha}a_0\times\left(\frac{V_{19}}{a_0}-M_0+\frac{T_{19}/T_0}{V_{19}/a_0}\frac{1-P_0/P_{19}}{\gamma_c}\right) \tag{1}$$

$$S=\frac{f}{(1+\alpha)F/\dot{m}_0} \tag{2}$$

$$\eta_P=\frac{2M_0\left[(1+f)V_9/a_0+\alpha\left(V_{19}/a_0\right)-(1+\alpha)M_0\right]}{(1+f)\left(V_9/a_0\right)^2+\alpha\left(V_{19}/a_0\right)^2-(1+\alpha)M_0^2} \tag{3}$$

$$\eta_T=\frac{a_0^2\left[(1+f)(V_9/a_0)^2+\alpha(V_{19}/a_0)^2-(1+\alpha)M_0^2\right]}{2fh_{PR}} \tag{4}$$

$$\eta_o=\eta_P\eta_T \tag{5}$$

The control system of the engine must operate in such a way that pressure ratio and mass flow rate to the compressor and fan are kept under the maximum design levels. Otherwise, the exit temperature of combustion chamber decreases in order to control the above-mentioned values at design values. This issue has been fully dealt with in [40].

5. THE STANDARD FORM OF MULTI-OBJECTIVE OPTIMIZATION PROBLEMS

In multi-objective optimization problems, the objective is to find design variable vector capable of optimizing objective function F(X) vector including P objective functions under k equal constraints h(X) and n unequal constraints g(X). Generally, it can be described as follows:

$$\begin{aligned}&\textit{Optimize}\\&F(X)=[\,f_1(X),\,f_2(X),\ldots,\,f_p(X)]\\&X=[x_1,x_2,\ldots,x_m]\\&\text{under constraints:}\\&h_i(X)=0 \qquad i=1,2,\ldots,k\\&g_j(X)\le 0 \qquad j=1,2,\ldots,n\end{aligned} \tag{6}$$

The results consist of a set of non-dominating optimized design points called Pareto points. Some Pareto concepts can be defined as follows [9]. In the below definitions, it is assumed that all objective functions have to be minimized while maintaining the generalize ability of the definitions.

5.1. Pareto Dominance

The vector $U=[u_1,u_2,\ldots,u_p]\in\Re^k$ is dominant $V=[v_1,v_2,\ldots,v_p]\in\Re^k$ (it is shown by $U\prec V$) if and only if:

$$\forall i\in\{1,2,\ldots,p\},u_i\le v_i\wedge\exists j\in\{1,2,\ldots,p\}:u_j<v_j \tag{7}$$

The above phrase means that there is at least one u_j that is smaller than v_j while the rest of u s are smaller than or equal to the corresponding v s.

5. 2. Pareto Optimality A point in $X^* \in \Omega$ (Ω is the acceptable design area as long as it satisfies the equal and unequal constraints) is called optimal Pareto if and only if $F(X^*) \prec F(X)$. In other words:

$$\forall i \in \{1,2,...k\}, \forall X \in \Omega - \{X^*\}$$
$$f_i(X^*) \le f_i(X) \wedge \exists j \in \{1,2,...k\}: f_j(X^*) < f_j(X) \tag{8}$$

The above phrase means that the optimal X^* is called the optimal Pareto as long as another solution is not found which dominates X^*.

5. 3. Pareto Optimal Set For a multi-objective optimization problem, a Pareto optimal set P^* includes all the optimal Pareto design vectors:

$$P^* = \{X \in \Omega | \nexists X' \in \Omega : F(X') \prec F(X)\} \tag{9}$$

In other words, there is no X' in Ω set which can dominate each $X \in P^*$.

5. 4. Pareto Front In a multi-objective problem, PF^* refers to a set of objective functions vector derived from design variables vector in Pareto set

$$PF^* = \{F(X) = (f_1(X), f_2(X),..., f_k(X)) : X \in P^*\} \tag{10}$$

5. 5. Pareto Optimal Points A set of optimal points is called Pareto optimal points if for each two points of A and B of this set, any improvement in the status of one of the objective functions leads to an impairment in at least one of the other objective functions while moving from A to B (or vice versa). In other words, no movement from A to B (or vice versa) leads to an improvement in the status of an objective function unless it leads to an impairment of one of the other objective functions.

6. NON DOMINATED SORTING GA-II (NSGA-II)

The Pareto-based approach of NSGA-II [16] has been recently used in many engineering MOPs because of its simple yet efficient non-dominance ranking procedure in yielding different level of Pareto frontiers .The sketch of NSGA-II is shown in Figure 3.

However, the crowding approach in such state-of-the-art MOEA is not efficient as a diversity-preserving operator, particularly in problems with more than two objective functions. As mentioned at introduction in [21] a new method has been presented to modify NSGA-II, so it can be safely used for any number of objective functions. In this study, such a modified MOEA is then used for thermodynamic optimization of turbofan engines.

7. OPTIMAL THERMODYNAMIC DESIGN OF TURBOFAN ENGINE

The objective of this section is to determine the input parameters of a turbofan engine in order to achieve the thermodynamic design of an engine which is capable of producing the maximum specific thrust while take-off, minimizing thrust specific fuel consumption and maintaining maximum efficiencies while cruising. Since the performance functions have to be calculated at performance points of take-off and cruise, take-off conditions and cruising conditions are considered as design conditions and off-design conditions, respectively [36]. Optimization is done in two and three objective modes between specific thrust function at take-off and the other functions at cruise condition. The following values have been used in the optimization:

7. 1. The Results of Optimization with two Objective Functions Figures 4 to 7 depict two-by-two Pareto Fronts resulting from the optimization of specific thrust at take-off with the other objective functions while cruising. The validity of Pareto fronts can be verified by comparing the maximum and minimum points of each individual objective function which have been yielded from performance curves presented in references [31, 36, 37] and have been presented in Table 1.

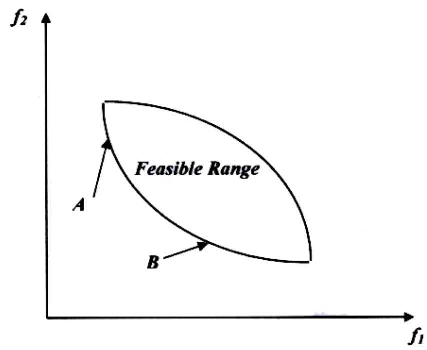

Figure 2. Pareto optimal points

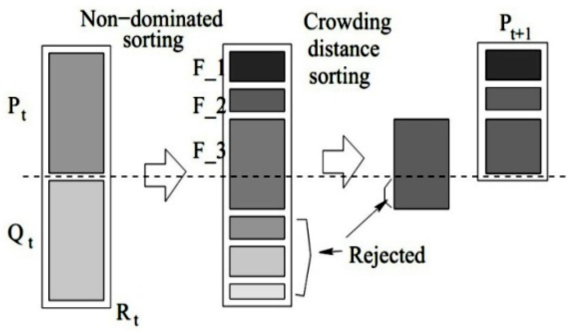

Figure 3. The sketch of NSGA-II [19].

TABLE 1. Optimal points achieved from each individual performance curve [34],[39-40].

$4 \le \pi_{cH} \le 8 \quad 2.5 \le \pi_{cL} \le 4 \quad 1.5 \le \pi_f \le 2.5 \quad 5 \le \alpha \le 12$

$\max(F/\dot{m}_0) = 447.8375(N/kg/s)$	$\max(\eta_T) = 0.951$
$\min(S) = 17.68((mg/s)/N)$	$\max(\eta_P) = 0.8708$
	$\max(\eta_o) = 0.2375$

The Pareto front of specific thrust and specific fuel consumption is presented in Figure 4. The specific thrust changes in the range of 296.5973 (N/Kg/s) to 445.525 (N/Kg/s). The specific fuel consumption changes in the range of 17.7019 mg/(N.s) to 20.6929 mg/(N.s). All the presented points are optimal design points. As it can be seen, these points are non-dominated i.e. if one moves to the right side of the curve, as the specific thrust increases the specific fuel consumption increases as well. From Figure 4, the design parameters are chosen in order to minimize fuel consumption for an optimized thrust. Figure 5 illustrates the Pareto front of specific thrust and thermal efficiency. As it can be seen, as the specific thrust increases, thermal efficiency decreases. Specific thrust in the range of 350 (N/kg/s) to 400 (N/kg/s) which corresponds to thermal efficiency in the range of 0.22 to 0.24 might be an appropriate design range. Figure 6 illustrates the Pareto front of specific thrust versus propulsive efficiency. If the design variables are chosen based on the left endpoint of the curve, specific thrust will be 296.54 (N/kg/s) and the resulting propulsive efficiency will be 0.8685. However, if instead of this point, the first break point of the curve which corresponds to specific thrust of 399.9453 (N/kg/s) and propulsive efficiency of 0.8446 is chosen, for a maximum decrease of 3% in propulsive efficiency, specific thrust will be 1.35 times higher. The mentioned point might be an appropriate design point. An analysis similar to that of Figure 5 may be presented for Figure 7.

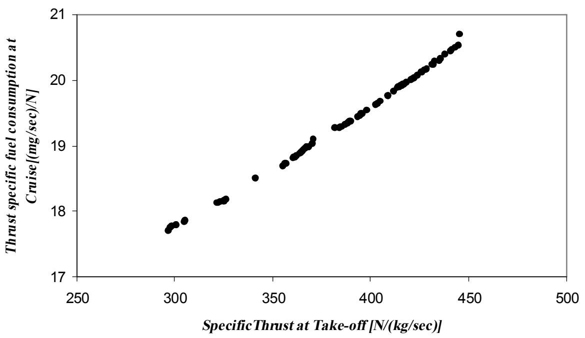

Figure 4. Pareto Front: Thrust specific fuel consumption & Specific Thrust

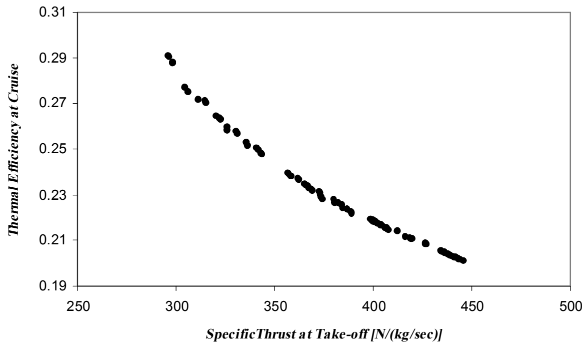

Figure 5. Pareto Front: Thermal Efficiency & Specific Thrust

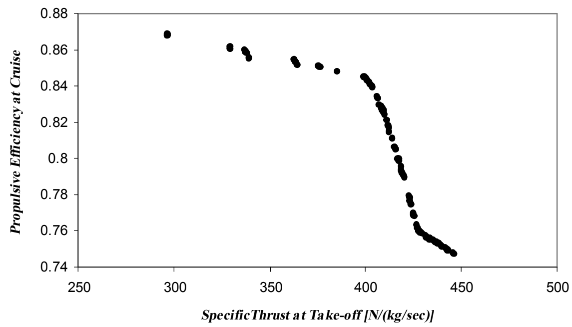

Figure 6. Pareto Front: Propulsive Efficiency & Specific Thrust

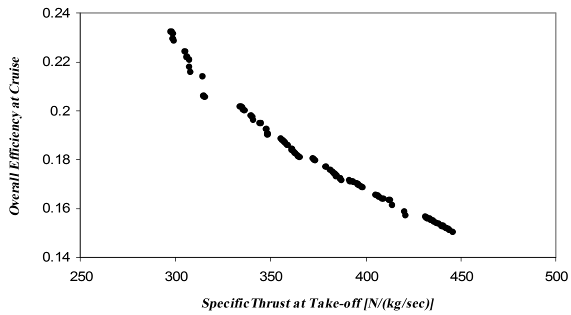

Figure 7. Pareto Front: Overall Efficiency & Specific Thrust

7. 2. The Results of Optimization with Three Objective Functions

In this section, the three functions of specific thrust, thrust specific fuel consumption and overall efficiency are considered as objective functions. The optimal design variables are determined in a way that the turbofan engine maintains the maximum overall efficiency and minimum thrust specific fuel consumption while cruising for the maximum specific thrust at take-off. The results which are presented in Table 2 are sorted based on specific thrust decrease. The key to verifying the correctness of the solutions is to find single-objective solutions or nearby values. The optimal values of objective functions specific thrust, thrust specific fuel consumption, and overall efficiency are presented in rows 1, 107, 111 of Table 2, respectively. The correctness of results might be verified by comparing the above-mentioned values and the values from Table 1. To use this table, the designer, according to the desired range of specific thrust, should find the two endpoints of the range in the table and reads the remaining objective functions. The desighner also chooses the best performance point of the engine and derives the values of design variables which generate the desired values for objective functions using the columns π_{cH} , π_{cL} , π_f and α . According to what herein before mentioned, the rows 92 to 107 might be appropriate for designing since specific thrust is within the range of 300 (N/kg/s) to 330 (N/kg/s), overall efficiency is within the range of 0.183 to 0.2238, and thrust specific fuel consumption is within the range of 17.7729 mg/(N.s) to 18.8845 mg/(N.s). However, the designer may use other ranges in the table in order to fulfill other purposes such as less fuel consumption. The table clearly shows, in the most of the cases, the better values of overall efficiency correspond to the better values of thrust specific fuel consumption. .

TABLE 2. Optimized objective functions and design variables in Turbofan engines

No	$F/\dot{m}_0\,(N/kg/s)$	$S\,(mg/s)/N$	η_o	π_{cH}	π_{cL}	π_f	α
1	447.4036	21.4707	0.145	7.99	3.9324	2.4817	5.0061
2	445.9262	20.5546	0.1504	7.9899	3.9918	2.499	5.0061
3	444.3184	20.5165	0.1511	7.9899	3.9918	2.499	5.0502
4	443.7915	20.5047	0.1513	7.9899	3.9918	2.499	5.0647
5	443.2117	20.4918	0.1516	7.9899	3.992	2.499	5.0806
6	440.3643	20.4349	0.1528	7.9899	3.992	2.499	5.1589
7	439.2339	20.4151	0.1532	7.9899	3.992	2.499	5.19
8	437.707	20.3563	0.1539	7.9899	3.9918	2.499	5.2319
9	436.8427	20.3376	0.1543	7.9899	3.992	2.499	5.2557
10	436.3833	20.328	0.1545	7.9899	3.992	2.499	5.2683
11	435.2145	20.3043	0.155	7.9899	3.9918	2.499	5.3003
12	431.8095	20.2403	0.1564	7.9899	3.992	2.497	5.3934
13	428.3742	20.2039	0.1558	7.9899	3.9918	2.3407	5.4733
14	427.9417	20.1927	0.156	7.9899	3.9918	2.3407	5.487
15	425.7409	20.101	0.1582	7.9899	3.9924	2.4189	5.5697
16	423.7547	20.0636	0.1591	7.9899	3.9924	2.4189	5.6278
17	421.8795	20.0274	0.1589	7.9899	3.9918	2.3407	5.6791
18	420.1534	19.986	0.1597	7.9899	3.9918	2.3407	5.7338
19	419.2892	19.9662	0.1602	7.9899	3.9918	2.3407	5.7611
20	417.5797	19.929	0.161	7.9899	3.9918	2.3407	5.8151
21	416.5625	19.9081	0.1615	7.9899	3.9918	2.3407	5.8472
22	415.8202	19.8935	0.1619	7.9899	3.9918	2.3407	5.8705
23	415.0082	19.892	0.1612	7.9899	3.9918	2.2781	5.8864
24	414.5509	19.8802	0.1615	7.9899	3.9918	2.2781	5.9019
25	413.0902	19.8453	0.1632	7.9899	3.9918	2.3407	5.9559
26	411.4364	19.8193	0.1631	7.9899	3.9918	2.3407	6.0072
27	410.6312	19.7868	0.1635	7.9899	3.9918	2.2781	6.0339
28	407.2934	19.719	0.1652	7.9899	3.9918	2.2781	6.1456
29	406.9066	19.712	0.1654	7.9899	3.9918	2.2781	6.1584
30	406.0155	19.6966	0.1659	7.9899	3.9918	2.2781	6.188
31	404.8674	19.6773	0.1657	7.9899	3.9918	2.2781	6.226
32	404.037	19.6633	0.1652	7.9899	3.9918	2.2781	6.2533
33	403.0698	19.6656	0.1656	7.9899	3.9918	2.1773	6.2684
34	402.1313	19.8086	0.166	7.7396	3.7964	2.2351	6.3491
35	401.737	19.6291	0.1663	7.9899	3.9918	2.1773	6.3186
36	400.9705	19.6254	0.1664	7.9899	3.9918	2.1617	6.3394
37	400.4561	19.6111	0.1667	7.9899	3.9918	2.1617	6.3591
38	399.5916	19.6789	0.1668	7.9899	3.8168	2.1773	6.4167
39	399.1257	19.5622	0.1678	7.9899	3.9918	2.1773	6.4167
40	396.0952	19.6426	0.1686	7.5024	3.9918	2.1773	6.5541
41	395.4477	19.4801	0.1699	7.9899	3.9918	2.1773	6.5541
42	394.7113	19.4657	0.1703	7.9899	3.9918	2.1773	6.5815
43	393.2862	19.4375	0.1708	7.9899	3.9918	2.1617	6.6325
44	391.7585	19.408	0.1713	7.9899	3.9918	2.1617	6.6901
45	391.3549	19.4003	0.1711	7.9899	3.9918	2.1617	6.7053
46	390.9306	19.3922	0.1708	7.9899	3.9918	2.1617	6.7212
47	390.2812	19.3797	0.1704	7.9899	3.9918	2.1617	6.7455

TABLE 2. Optimized objective functions and design variables in Turbofan engines (continued)

No	$F/\dot{m}_0\ (N/kg/s)$	$S\ (mg/s)/N$	η_o	π_{cH}	π_{cL}	π_f	α
48	385.833	19.2962	0.1674	7.9899	3.9918	2.1617	6.9096
49	385.8157	19.293	0.1675	7.9899	3.9973	2.1617	6.9096
50	384.7135	19.3831	0.1714	7.9899	3.9918	1.997	6.8655
51	383.7862	19.4093	0.1722	7.9899	3.9918	1.997	6.9089
52	381.4586	19.3363	0.1737	7.9899	3.9918	1.997	7.0183
53	379.7038	19.287	0.1749	7.9899	3.9918	1.997	7.101
54	377.7424	19.2046	0.1762	7.9899	3.9918	1.997	7.1936
55	376.8229	19.1763	0.1768	7.9899	3.9918	1.997	7.237
56	375.6642	19.1417	0.1776	7.9899	3.9918	1.997	7.2917
57	374.9982	19.1225	0.1781	7.9899	3.9918	1.997	7.3231
58	373.837	19.0903	0.1789	7.9899	3.9918	1.997	7.3778
59	372.1617	19.0469	0.18	7.9899	3.9918	1.997	7.4565
60	371.5136	19.0312	0.1805	7.9899	3.9918	1.997	7.4868
61	366.7805	18.9218	0.1788	7.9899	3.9918	1.997	7.7059
62	364.5063	19.0061	0.1822	7.9899	3.9918	1.9032	7.733
63	363.8526	18.9834	0.1827	7.9899	3.9918	1.9032	7.7684
64	361.2011	18.9989	0.1834	7.9899	3.9914	1.872	7.857
65	360.0009	18.9619	0.1843	7.9899	3.9914	1.872	7.9253
66	359.5916	18.95	0.1847	7.9899	3.9914	1.872	7.9487
67	358.3122	18.8104	0.187	7.9899	3.9918	1.9032	8.0686
68	357.5064	18.7888	0.1876	7.9899	3.9918	1.9032	8.112
69	355.6992	18.7568	0.1886	7.9899	3.9918	1.8927	8.1988
70	355.2722	18.7458	0.189	7.9899	3.9918	1.8927	8.2221
71	353.9106	18.6958	0.1865	7.9899	3.9918	1.9032	8.3041
72	352.4465	18.7812	0.189	7.9899	3.9914	1.8407	8.3041
73	350.2504	18.6029	0.1839	7.9899	3.9918	1.9032	8.4955
74	348.9241	18.609	0.1892	7.9899	3.9914	1.8716	8.5533
75	348.122	18.573	0.182	7.9899	3.9918	1.9029	8.6042
76	346.731	18.7564	0.1919	7.7462	3.9914	1.8091	8.6042
77	346.4799	18.6774	0.1927	7.9899	3.9914	1.8091	8.6042
78	346.0071	18.5319	0.187	7.9899	3.9914	1.8716	8.7143
79	345.609	18.6468	0.1935	7.9899	3.9914	1.8091	8.6596
80	344.329	18.6036	0.1946	7.9899	3.9914	1.8091	8.7409
81	343.8982	18.5896	0.195	7.9899	3.9914	1.8091	8.7683
82	343.3928	18.5736	0.1954	7.9899	3.9914	1.8091	8.8003
83	339.5605	18.4607	0.1959	7.9899	3.9914	1.8091	9.0417
84	337.6903	18.405	0.1944	7.929	3.9914	1.8091	9.1624
85	337.6187	18.3871	0.1945	7.9899	3.9914	1.8091	9.1624
86	336.4065	18.3625	0.1936	7.9899	3.9914	1.8091	9.2369
87	336.02	18.3555	0.1933	7.9899	3.9914	1.8091	9.2605
88	335.108	18.3401	0.1926	7.9899	3.9914	1.8091	9.3159
89	332.7682	18.2953	0.1905	7.9899	3.9914	1.8091	9.4556
90	332.3068	18.7251	0.1992	7.9865	3.5487	1.7344	9.4245
91	331.1081	18.2792	0.1901	7.9899	3.9914	1.8047	9.5538
92	330.5544	18.6578	0.201	7.9865	3.5487	1.7344	9.5538
93	329.8003	18.3586	0.2046	7.9899	3.9917	1.7344	9.5538
94	321.2242	18.5012	0.2048	7.9899	3.9945	1.6207	9.6986
95	316.9569	18.2714	0.183	7.9282	3.9857	1.7736	10.3934
96	316.813	18.8845	0.2049	6.1041	3.8581	1.6766	10.4739
97	315.8614	18.2036	0.1855	7.9899	3.9918	1.7628	10.4749
98	315.8445	18.2016	0.1855	7.9899	3.9973	1.7628	10.4749
99	314.7081	18.5677	0.2113	7.9899	3.6445	1.6221	10.3549
100	314.1896	18.3155	0.2144	7.9899	3.9945	1.6221	10.3549
101	308.1819	18.0565	0.2223	7.9899	3.9918	1.6238	10.9292
102	307.0281	18.0193	0.2237	7.9899	3.9945	1.6221	11.0289
103	306.4735	17.9986	0.224	7.9899	3.9945	1.6221	11.081

TABLE 2. Optimized objective functions and design variables in Turbofan engines (continued).

No	$F/\dot{m}_0\ (N/kg/s)$	$S\ (mg/s)/N$	η_o	π_{cH}	π_{cL}	π_f	α
104	306.0517	17.9825	0.2238	7.9899	3.9945	1.6221	11.1206
105	301.7555	17.8122	0.2214	7.9899	3.9918	1.6218	11.5185
106	301.3264	17.799	0.221	7.9899	3.9945	1.6221	11.5581
107	300.1217	17.7729	0.2202	7.9899	3.9918	1.6218	11.6667
108	297.3817	18.1166	0.2301	7.6126	3.7865	1.5789	11.8097
109	297.1528	17.9987	0.2315	7.9782	3.7865	1.5789	11.8097
110	297.1448	17.9951	0.2315	7.9899	3.7865	1.5789	11.8097
111	296.8151	17.8654	0.2331	7.9899	3.9916	1.5789	11.8097

8. CONCLUSION

The Modified NSGA-II has been employed for thermodynamic optimization of turbofan engine. This optimization process has been done with two and three objective functions. The results have been presented in two forms of Pareto Fronts and table. The results enable the designer to derive the desired parameters according to the flight objectives. In addition, the off-design model of turbofan engine is studied. Thus, it is possible to investigate the performance functions of turbofan engines in different take-off and cruise heights. The results of this paper are concluded as: For the maximum specific thrust at take-off simultaneously the minimum thrust specific fuel consumption and maximum efficiencies at cruising, the optimum design parameters have been chosen. Furthermore, the thrust specific fuel consumption and overall efficiency functions are not conflicted in large domain of performance at cruise and in the range of 300 (N/kg/s) to 400 (N/kg/s) of the specific thrust at take-off, the propulsive efficiencies variation at cruise is negligible.

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Optimal Thermodynamic Design of Turbofan Engines using Multi-objective Genetic Algorithm

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چکیده

در این مطالعه بهینه سازی توابع عملکردی موتورهای توربوفن مورد بررسی قرار می گیرد. برای انجام، بهینه سازی چند هدفی الگوریتم ژنتیک به مدل خارج از نقطه طراحیِ موتور توربوفن اعمال می شود. متغیرهای طراحی شامل نسبت فشارهای کمپرسور پرفشار، کمپرسورکم فشار، فن ونسبت کنار گذر می باشند. این متغیرها به گونه ای بدست می آیند که توابع عملکردی موتور توربوفن به طور همزمان در بهترین شرایط خود قرار گیرند. توابع عملکردی عبارتند از رانش ویژه درهنگام برخاست و مصرف ویژه سوخت، راندمانهای رانش، حرارتی وکلی در هنگام پرواز. این بهینه سازی توسط روش تصحیح شده NSGAII انجام می گیرد که از بهترین روشهای الگوریتم ژنتیک چند هدفی می باشد. نتایج حاصل از بهینه سازی چند هدفی شامل مجموعه ای از بردارهای جواب بوده که طراح با توجه به شرایط مساله یکی از بردارهای طراحی را انتخاب می نماید. انجام بهینه سازی چند هدفی بر روی مدل خارج از نقطه طراحیِ موتور توربوفن از نوآوری های این مقاله می باشد که برای اولین بار مورد مطالعه قرار گرفته است.

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