

Optimization

Multi-Objective Optimization

Problem

Pareto Concepts

Scilab Routines

Algorithm

Example and Solution

Multi-Objective Optimization

4 x - 3 - 3 x +11

n (2x2

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Presentation on Internship

17th July, 2009

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♦ Prelude

Internship Period

- Internship lasted from the first week of May until mid July, 2009 •
- Under the supervision of Mr. Désidéri •

 $b = 4x^{-2} = \frac{1}{2}(2x^{2}-3x+1)^{\frac{1}{2}}$

Objective

- The project I was involved in was related to the Multi-objective • optimization with the objective functions related to aeronautics
- The main task was to develop an algorithm in Scilab which can be used to find Pareto Optimal set and plot Pareto front

Abstract

- In aeronautics, performance of an aircraft depends upon several factors such as, lift, drag, moments. Also important is the structural integrity of the aircraft. But, often optimizing one of the criteria has adverse effects on the other
- To cater this issue, simultaneous optimization of all the important • factors need to be carried out

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Optimization in aerospace

• From the beginning, engineers in this field are eager to employ the optimization methods so as to save that extra inch

□ Multi-objective Optimization

- Multi-objective optimization has its root in late nineteenth century welfare economics, in the works of Edgeworth and Pareto
- Simply when there are two or more objective functions to be minimized
- Often these functions are contradicting in behavior
- Some examples can be found in following sectors
 - Bridge construction, Aircraft design, Chemical Plant design etc.

 $\Gamma \in (\infty)$

Mathematically

$$\min_{\mathbf{x} \in \mathbf{C}} F(\mathbf{x}) = \begin{cases}
f_1(\mathbf{x}) \\
f_2(\mathbf{x}) \\
\vdots \\
f_{n-1}(\mathbf{x}) \\
f_n(\mathbf{x})
\end{cases}$$

where $n \ge 2$

 $C = \{x : h(x) = 0; g(x) \le 0, a \le x \le b\}$

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Example and Solution Multi-objective optimization can be further classified depending upon the type of objectives involved:

- Multi-criterion Optimization
- Multi-point Optimization
- Multi-discipline Optimization
- In our problem, we deal with multi-discipline optimization problem

Multi-Disciplinary Optimization

- Optimization problem consists of objective functions from a variety of disciplines
- Presence in a number of fields, including automobile design, naval architecture, electronics, computers and electricity distribution
- Example: Boeing blended wing body (BWB) aircraft

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Pareto Optimality

- Important in Multi-objective optimization and a convenient representation
- Named after Vilfredo Pareto, it's a measure of efficiency
- Pareto Optimal solution is the one that cannot be further improved without hurting at least one player
- Such design vector x^{*} is called Pareto optimal
- The vectors x^{*} corresponding to the solutions included in the Pareto Optimal set are called "non-dominated"
- □ Dominance/Non-dominance • Y¹ is said to dominate the design point Y² Iff, for all J = J_A, J_B, ... $f(Y^1) ≤ f(Y^2)$ and at least one of the inequalities is strict • Otherwise, the vectors are said to be non-dominated $Y^1 > Y^2, Y^2 > Y^1$

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Pareto Front

- The plot of the objective functions whose non-dominated vectors are • in the Pareto optimal set is called the "Pareto Front"
- Useful in engineering •

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Convenient way of considering only Pareto efficient alternatives •



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Example and Solution Multi-objective optimization with 3 objective functions

- J_1 , J_2 and J_3
- Most probably related to aerodynamic design, structural, thermal and acoustics etc
- Each criterion is considered to be a smooth function of a common design vector $Y \in {I\!\!R}^4$

Problem Statement

Design vector

 $Y \in \mathbb{R}^N$

• Minimize the given criteria

 $= 4x^{-2} = 2(2x^{2}-3x+1)$

 $j_i(Y) \quad i=1,2,\ldots,n$

- Where
- $N \ge n$
- We consider N=4 and n=3
- The space of design vector can be a Hilbert Space usually equal to $R^{\rm N},$ but it can also be a subspace of L^2

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□ Some important concepts

- Y $\in \mathcal{H}$; \mathcal{H} : working space, a Hilbert space equal to $\mathbb{R}^{\mathbb{N}}$, can also be a subspace of \mathbb{L}^2
- The objective functions are assumed to be class C^2 in some working open ball of the design space \mathcal{H}

Lemma 1

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Let be a Pareto optimal point of the smooth criteria *I_i*(*Y*) (1 ≤ *i* ≤ *n* ≤ *N*) and define the gradient vectors *u_i⁰* = ∇*J_i*(*Y*⁰) in which denotes the gradient operator. There exists a convex combination of the gradient vectors that is equal to zero:

$$\sum_{i=1}^{n} \alpha_i u_i^0 = 0, \quad \alpha_i \ge 0, \quad \sum_{i=1}^{n} \alpha_i = 1$$

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Pareto Stationary

 The smooth criteria J_i(Y) are said to be Pareto stationary if they satisfy lemma 1, i.e.

$$\sum_{i=1}^{n} \alpha_{i} u_{i}^{0} = 0, \quad \alpha_{i} \geq 0, \qquad \sum_{i=1}^{n} \alpha_{i} = 1$$

- For smooth unconstrained criteria, Pareto stationarity is a necessary condition for Pareto optimality
- If the smooth criteria $J_i(Y)$ are not Pareto stationary at a given design point then descent directions common to all criteria exist

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Lemma 2

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Example and Solution Let *H* be a Hilbert space of finite or infinite dimension N, and
 {*u_t*}(1 ≤ *t* ≤ *n* ≤ *N*) a family of n vectors in *H*. Let *U* be the set of strict convex combinations of these vectors

$$\mathcal{U} = \left\{ \omega \in \mathcal{H} \middle/ \omega = \sum_{i=1}^{n} \alpha_{i} u_{i} ; \alpha_{i} > 0 ; \sum_{i=1}^{n} \alpha_{i} = 1 \right\}$$

• and \overline{u} its closure (the convex hull of the family). Then, there exists a unique element of minimum norm, and:

 $\forall \overline{u} \in \overline{\mathcal{U}} : (\overline{u}, \omega) \ge (\omega, \omega) = \|\omega\|^2 := C_{\omega}$

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Example and Solution

Theorem 1

 Let H be a Hilbert space of infinite or finite dimension N. Let
 *I*_i(Y) (1 ≤ *i* ≤ *n* ≤ *N*) be n smooth functions of the vector Y ∈ H, and Y⁰
 a particular admissible design point, at which the gradient vectors are
 denoted by u⁰_i = ∇*J*_i(Y⁰) and,

$$\mathcal{U} = \left\{ \omega \in \mathcal{H} \middle/ \omega = \sum_{i=1}^{n} \alpha_{i} u_{i} ; \alpha_{i} > 0 ; \sum_{i=1}^{n} \alpha_{i} = 1 \right\}$$

- Let ω be the minimal norm element of the convex hull \overline{u} , closure of U. Then:
 - Either ω = 0, and the criteria are Pareto stationary at Y = Y⁰
 - Or ω ≠ 0 and ω is a descent direction common to all the criteria; additionally, if ω∈U, the inner product (\overline{u}, ω) is equal to $||\omega||^2$ for all $\overline{u} \in \overline{u}$

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Example and Solution

- - Solve non-linear optimization problem •
 - Can define the prefered algorithm to solve the problem
 - But, allows constraints in the form of lower and upper bounds on design variable **only**
 - Can only define lower bound not the upper bound

Quapro/Qpsolve

- Older version of Scilab has guapro, now replaced by gpsolve in recent versions
- Used for objective function consisting of a guadratic form plus a linear • combination of the design variables
- Constraint functions can be defined in addition to bounds on design variable
- The constraints functions should be linear
- But the matrix describing the quadratic part of objective function • should be only positive definite symmetric matrix
- We cannot guarantee the positive definitivity GDANSK

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Example and Solution

Minimization problem

$$\omega = \sum_{i=1}^{n} \alpha_i u_i^0$$

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Minimize

Subject to constraints

$$a_i \ge 0 (\forall i); \sum_{i=1}^n a_i = 1$$

 $\min_{\alpha \in \mathbb{R}^n} \left| \sum_{i=1}^n \alpha_i u_i^0 \right|^2$

Initial step

Choose a design vector Y^0 and make an initial guess on α •

$$\alpha^{0} = \left[\frac{1}{n}, \frac{1}{n}, \dots, \frac{1}{n}\right]$$

- Our case, n = 3 and N = 4•
- BAUKCEROSA NUCE $H\alpha^0 = \begin{bmatrix} 1 & 1 & 1 \\ \frac{1}{2}, \frac{1}{2}, \frac{1}{2} \end{bmatrix}$ **GDANSK** SAGUERAS -

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Criteria and derivatives at Y⁰ **Prelude** $I_i(Y^0) (1 \le i \le n \le N)$ $u_i^0 = \nabla I_i(Y^0)$ **Optimization** Design of Experiment **Multi-Objective** • Proposed by Ronald A. Fisher, in his innovative book The Design of **Optimization** Experiments (1935) Problem Design of all information-gathering exercises where variation is present Pareto Purpose of it is to study the effect of some processes or intervention Concepts on some objects Scilab Routines \Box Check condition on ω , i.e. If $\omega = 0$, stop, that is it is already a Pareto optimal point • Algorithm • If $\omega \neq 0$, ω is the descent direction **Example and** Solution RAILEEONA NICE HAMBURG ISACHUEASS GOANSK

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$$\Box$$
 Redefine, ω as

$$\omega = \sum_{i=1}^{n-1} \alpha_i u_i^0$$

$$q = \min_{\alpha \in \mathbb{R}^{n-1}} \|\omega\|^2 = \min_{\alpha \in \mathbb{R}^{n-1}} \left\| \sum_{i=1}^{n-1} \alpha_i u_i^p \right\|^2$$

Constraints take the following new form

$$\alpha_i \geq 0 \; (\forall i) \; ; \; \alpha_n = 1 - \sum_{i=1}^{n-1} \alpha_i$$

• Define Partial derivatives of q w.r.t. A

$$\frac{\partial q}{\partial \alpha_i} = 2(\omega, u_i^0 - u_n^0) \quad \forall i = 1, 2, \dots n - 1$$

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□ For i = 1,..., n-1

Define a' as

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• a' can be set to value either 0 or 1 depending on the condition and then ρ can be defined as

$$\frac{\partial q}{\partial \alpha_i} \ge 0 \quad \Rightarrow \rho_i \le \frac{\alpha_i^0}{\partial \alpha_i} \\ \frac{\partial q}{\partial \alpha_i} < 0 \quad \Rightarrow \rho_i \le \frac{1 - \alpha_i^0}{\partial \alpha_i} \\ \frac{\partial q}{\partial \alpha_i} < 0 \quad \Rightarrow \rho_i \le \frac{1 - \alpha_i^0}{\partial \alpha_i} \\ \frac{\partial q}{\partial \alpha_i}$$

 $1 - \alpha_{i}^{0}$ /

Summarizing

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$$\rho_{i,max} = \cdot$$

 $\partial \alpha_i$

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□ Set design variable as

• For every point in the interval [0, tmax], $Y^0 = Y^0 - t\omega$

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- The step size should be such that it is the largest strictly positive real number for which all the functions are monotone-decreasing over the interval [0,t_{max}]
- Continue until increase in any one of the criteria is encountered

 $j_i(t) = J_i(Y^0 - t\omega) \ (1 \le i \le n)$

□ This is our updated design vector

- Set this new design vector as Y⁰ and start anew the whole process from the beginning
- Continue until the condition on ω is satisfied

 $|\omega| < tol$ stop

This results in one point on the Pareto Optimal set

And then evaluate the criteria at each new vector

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Example and Solution Criteria J1, J2 and J3 $J_1(y) = 2\left((2+\sqrt{2})y_1^2 + \sqrt{2}y_3^2 + y_4^2\right)$ $I_2(y) = 3\left(\frac{5}{3y_1^2} + \frac{3}{2y_2^2} + \frac{2}{y_3^2} + \frac{2}{y_4^2}\right)$ $J_3(y) = \frac{1}{y_1^2} + \frac{2}{y_2^2} + \frac{2}{y_3^2} + \frac{1}{4y_4^2}$

 $\Box \text{ Set of design variables}$ $Y = \left\{ \begin{bmatrix} 0.9\\ 0.9\\ 0.9\\ 0.9 \end{bmatrix}, \begin{bmatrix} 1\\ 1\\ 1\\ 1\\ 1 \end{bmatrix}, \begin{bmatrix} 1.2\\ 1.2\\ 1.2\\ 1.2 \end{bmatrix}, \begin{bmatrix} 1.3\\ 1.3\\ 1.3\\ 1.3\\ 1.3 \end{bmatrix}, \begin{bmatrix} 1.4\\ 1.4\\ 1.4\\ 1.4 \end{bmatrix}, \begin{bmatrix} 1.6\\ 1.6\\ 1.6 \end{bmatrix}, \begin{bmatrix} 1.7\\ 1.7\\ 1.7\\ 1.7 \end{bmatrix}, \begin{bmatrix} 1.8\\ 1.8\\ 1.8\\ 1.8 \end{bmatrix}, \begin{bmatrix} 1.9\\ 1.9\\ 1.9 \end{bmatrix}, \begin{bmatrix} 2.0\\ 2.0\\ 2.0 \end{bmatrix} \right\}$ DARCELONA NICE HAMBURG LAQUILA GOANSK

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RII	V R		$4x^{2}x^{2}$ = 2 (22-3x+1)^{2} = 8 (2x)	$\frac{1}{2} = \frac{1}{2} = \frac{1}$	4 cree 3 2 roct - 3 1222 - 324, Jack - 1222 - 324, Jack	tom kx = Multi ax dx = Opti	Objectiv
Prelude		Results for vectors	first iteral	tion for the	e complete	set of desi	gn
Optimization		×.	initial	:2	:2		
Aulti-Objective Optimization		Y	1	J2	J3	W	
Problem		0.9	9.442052 11.65685	26.54321 21.5	6.481481 5.25	8.258974 6.020793	
Pareto		1.1 1.2	14.10479 16.78587	17.7686 14.93056	4.338843 3.645833	4.523512 3.484256	
Scilab		1.3	19.70008 22.84743	12.72189 10.96939	3.106509 2.678571	2.740463	
Algorithm		1.6	29.84155	8.398438	2.050781	20.14365	
Example and		1.7	33.68831 37.76821	6.635802	1.816609 1.62037	22.29636 24.35648	
Solution		1.9	42.08124	5.955679	1.454294	26.33168	

RII	V R		$4x^{2}x^{2}$ $2(2x^{2}x^{2}x^{2})^{2}$ $8(2x^{2})^{2}$	$\frac{1}{2} = \frac{1}{2} = \frac{1}$	1 1 2 2 2 3 2 + 1 J Sec	ton kx = Mult	i-Objective imization
		Results for	· last iterat	ion for the	complete	set of desi	an
Prelude	-	vectors					911
Optimization		Y	final	i2	i3	w	
Multi-Objective Optimization			J-	j -	<u> </u>		
Problem		0.9	32.73655 33.25493	8.294122 8.20128	1.562837 1.548888	0.906045 0.894161	
Paroto		1.1	32.3329	8.233263	1.603136	0.945527	
Concepts		1.2	31.38221	7.985843	1.595362	0.944998	
Scilab Routines		1.3	33.62845	7.48323	1.603102	0.96563	
Algorithm		1.6	29.00605	7.39153	1.333886	0.918005	
Example and		1.7	29.05121	8.738566	1.460697	0.88562	
Solution		1.9	14.92747	12.59104	2.556135	0.813994	
	M Uari	2	29.67797	7.391229	1.356703	0.892021	867

