Isoperformance: Analysis and Design of Complex Systems with Known or Desired Outcomes

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Abstract. Tradeoffs between performance, cost and risk frequently arise during analysis and design of complex systems. Many such systems have both human and technological components and can be described by mathematical input-output models. Oftentimes such systems have known or desired outcomes or behaviors. This paper proposes "isoperformance" as an alternative approach for analyzing and designing systems by working backwards from a set of desired performance targets to a set of acceptable solutions. This is in contrast to the traditional "forward" process, which starts first in the design space and attempts to predict performance in objective space. Isoperformance can quantify and visualize the tradeoffs between determinants (independent design variables) of a known or desired outcome. For deterministic systems, performance invariant contours can be computed using sensitivity analysis and contour following. In the case of stochastic systems, the isoperformance curves can be obtained by regression analysis, given a statistically representative data set. Examples from opto-mechanical systems design and human factors are presented to illustrate specific applications of the method.

Definition

Isoperformance is a methodology for obtaining a performance invariant set of analysis or design solutions. These solutions approximate performance invariant contours or surfaces based on an empirical or deterministic system model. The word *isoperformance* by itself is used interchangeable with *the isoperformance approach*.

Introduction

> "The experience of the 1960's has shown that for military aircraft the cost of the final increment of performance usually is excessive in terms of other characteristics and that the overall system must be optimized, not just performance."
>
> AIAA Technical Committee on Multidisciplinary Design Optimization (MDO)
> White Paper on Current State of the Art (Schrage et al. 1991)
> January 15, 1991

This introductory quote suggests that while performance is a central aspect of systems analysis and design, there are other important factors to consider. A system is understood broadly as a complex set of human or technological components that interact to achieve a desired function. Performance is a quantitative measure of how well this function is executed. Four of the main tensions during system or product development have been identified (Maier and Rechtin 2000) and are shown in Figure 1.

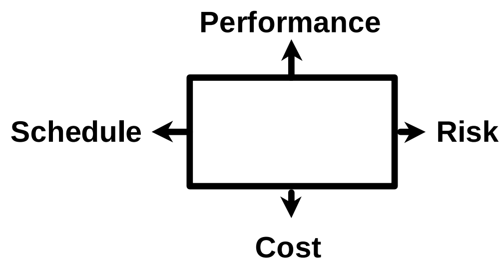


Figure 1. Tensions during systems architecting and design (Maier and Rechtin 2000, p.83)

One of the important tasks of a system of program manager is to identify, quantify and resolve these tensions. An increase in system performance can generally only be achieved by increasing cost, stretching project schedules, accepting a higher level of risk or a combination thereof.[1] It is not immediately obvious what the "success" criteria of a system are, but it is generally said that a successful system "meets the performance requirements" (Shishko, 1995).

Ignoring for a moment the more subtle aspects of schedule and risk we may want to discuss the relationship between system cost and performance. A traditional approach is to fix the amount of resources available (costs) and to maximize the system performance given this constraint. A second approach, the one considered in this paper, is to fix the desired performance level – assuming that such a desired level is known - and to find a design or a set of designs that will achieve it at minimal cost. This leads naturally to the concept of "isoperformance".

The next section will frame the isoperformance problem in a generic way, while the third section describes techniques for finding the performance invariant set in a bounded design space. Next we discuss the deterministic design problem using a spacecraft example, followed by demonstration of the stochastic isoperformance approach using a human factors example presented by Kennedy and Jones (1990, 1996, and 2000). Conclusions and recommendations for future research complete the discussion.

Posing the Isoperformance Problem

A number of researchers such as Taguchi, Cook (1997) and Messac (1996) have recognized that system requirements typically fall into one of three classes: "smaller-is-better" (SIB), "larger-is-better" (LIB) and "nominal-is-better" (NIB), see Figure 2. In automotive design for example a

[1] It is interesting to note that NASA's *faster-better-cheaper* initiative in the 1990's attempted to develop systems that where built in less time (schedule), had improved technical characteristics (performance) and lower lifecycle cost. However, mission failures such as Mars Polar Lander and Deep Space 2 can be directly attributed to neglecting the risk aspect (Young et al., 2000).

target vehicle range [km] must be achieved (NIB), specific fuel consumption [mpg] must be minimized (SIB) and interior roominess [m^3] must be maximized (LIB). Typically these objectives are counteracting. Large interior volume would tend to increase drag, which in turn decreases range and increases specific fuel consumption. A target vehicle range can be achieved by trading off fuel capacity, empty weight and engine displacement among others. The isoperformance approach assumes that desired performance targets are known, i.e. that the key performance objectives are captured as NIB. If the system performance is significantly above the target value, $J_{i,req}$, the system is considered to be overdesigned, on the other hand if the system performance is significantly below the target value the system design is unacceptable.

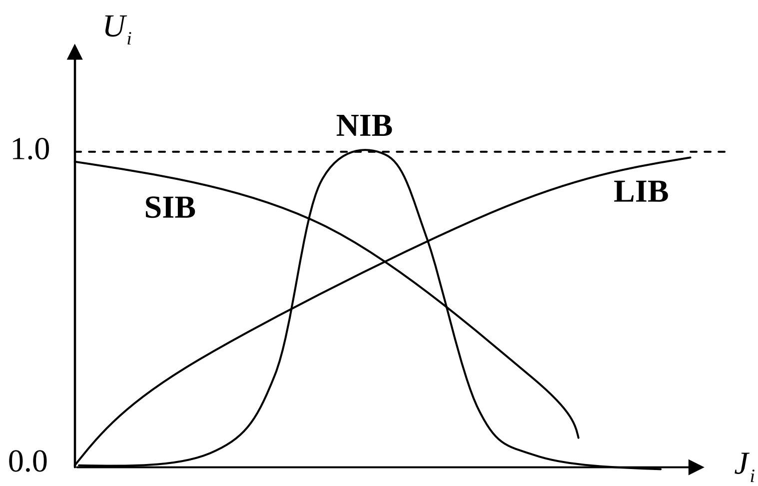


Figure 2: Normalized utility curves U_i of the i-th system objective, J_i, represented by a monotonically decreasing (SIB), increasing (LIB) and concave function (NIB)

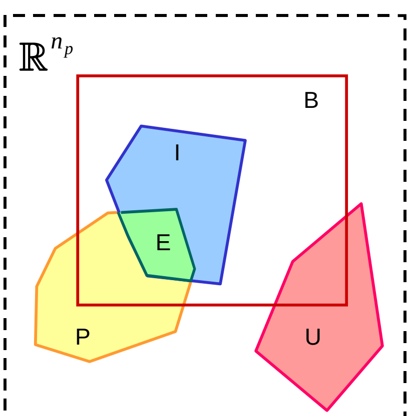
Traditional performance maximization always assumes (LIB) at the expense of the other dimensions. Isoperformance on the other hand fixes the amount of performance at an acceptable level (NIB) and trades off the other directions with respect to each other. The problem may be posed in two different ways: as a multiobjective optimization problem with performance equality constraints or as an isoperformance problem, see Table 1.

Multiobjective Optimization	Isoperformance Problem
$\min \mathbf{J}_{cr}(\mathbf{x}) = \left[J_c(\mathbf{x}) \quad J_r(\mathbf{x}) \right]^T$ s.t. $J_z(\mathbf{x}) = J_{z,req}$ $g(\mathbf{x}) \le 0$, $h(\mathbf{x}) = 0$ $\mathbf{x_{LB}} \le \mathbf{x} \le \mathbf{x_{UB}}$	1. find $\mathbf{x_{iso}} \in \mathbf{I}$ s.t. $\mathbf{I} = \left\{ \mathbf{x} \middle\| J_z(\mathbf{x}) \approx J_{z,req} \right\}$ $g(\mathbf{x}) \le 0$, $h(\mathbf{x}) = 0$ $\mathbf{x_{LB}} \le \mathbf{x} \le \mathbf{x_{UB}}$ 2. find $\mathbf{E} = \left\{ \mathbf{x^*_{iso}} \middle\| \mathbf{J}_{cr}(\mathbf{x^*_{iso}}) \le \mathbf{J}_{cr}(\mathbf{x}) \ \forall \ \mathbf{x} \in \mathbf{I} \right\}$ 3. select $\mathbf{x^{**}_{iso}} \in \mathbf{E}$

Table 1. Multiobjective Optimization versus Isoperformance Problem Formulation

The left side of Table 1 shows the traditional multiobjective design optimization problem, where we attempt to simultaneously minimize system cost J_c and risk J_r, which are functions of the vector of design (decision) variables, **x**. Jones (1996, 2000) calls these design variables "determinants". This minimization is subject to performance equality constraints, general inequality constraints g and equality constraints h, as well as side constraints $\mathbf{x_{LB}}$ and $\mathbf{x_{UB}}$. Oftentimes the objective is scalarized by introducing weighting factors. In the case of scalar cost and risk metrics one may write $J_{cr} = wJ_c + (1-w)J_r$, where w is a weighting factor that is allowed to vary between 0 and 1. This allows a trade between cost and risk. Solving this optimization problem will *yield only a single optimal design*, **x*,** provided there is a non-zero feasible region.

The right side of Table 1 shows the setup of the equivalent isoperformance problem. The solution of this problem requires a three step procedure. First, design vectors $\mathbf{x_{iso}}$, which approximate the performance-invariant set **I** are found. All elements of this set meet the performance equality as well as other constraints. Depending on the algorithm used (de Weck, 2002) one is left with a set of design points that all perform equally well in terms of performance J_z. The cost and risk of these designs, $\mathbf{J}_{cr}(\mathbf{x}_{iso})$, is then evaluated and the efficient subset **E** is identified (step 2). The efficient set **E** contains only non-dominated (i.e. Pareto optimal) solutions. The original concept of Pareto (1906) optimality or "best tradeoff" comes from the field of economics and gradually migrated into the Engineering Sciences in the second half of the 20th century. Non-dominated solutions are those that are not dominated in all cost and risk objectives by any other member of the set. In the third step, the final design $\mathbf{x_{iso}}$****** is chosen from the efficient set **E** based on engineering reasoning and stakeholder consensus.
Another way to view the isoperformance approach is set theory as shown in Figure 3. The first task is to find the elements of the isoperformance set **I** in **B**, where **B** is the set that fulfills prime feasibility. Since the performance requirements are bounded, it is true that the intersection of **U** an **I** is zero. In other words only stable solutions can be part of the isoperformance set **I**. The ultimate goal is to find a family of designs $\mathbf{x_{iso}}$, which are elements of the efficient set **E**. The efficient set is the intersection of the isoperformance set **I** and the Pareto optimal set **P**. A fundamental assumption is that the design (decision) variables in **x** are continuous.



Set	Description
$\mathbb{R}^{n_p}$	**n_p-dimensional real valued Euclidean vector space**
B	**Subset of $\mathbb{R}^{n_p}$, bounded by parameter constraints**
I	**Subset of B, which satisfies isoperformance condition**
U	**Unstable subspace, where** $\max(\mathrm{Re}(\lambda_i)) > 0$
P/E	**Pareto optimal and efficient set**

Figure 3. Set theoretical view of Isoperformance, λ_i are the system eigenvalues[2]

[2] The number of design variables is n_p or n_x

The question regarding which of these two approaches is superior for the design of complex Engineering Systems is not easy to answer. It is, however, well known that most optimization algorithms experience significant difficulties and computational expense while enforcing multiple equality constraints. Secondly, we only expect a single point design as the solution of the multiobjective optimization problem. Thirdly, the process is highly dependent on how the weighting factors w are chosen and finally it must be said that the traditional design optimization process is similar to "push-button" design, i.e. the stakeholders don't gain much insight in how the solution was obtained.

The isoperformance approach on the other hand decouples the problem into three phases that allow system analysts and designers to develop intuition about system tradeoffs that would otherwise remain hidden. The approach does not rely on stakeholder preferences except for the selection of the final design**,** $\mathbf{x}_{iso}$****,** from the efficient set **E**. Also, instead of presenting a single optimal system design, the isoperformance approach provides a family of potential designs that do not distinguish themselves by the performance they achieve, but rather by their varying cost and risk characteristics. For these reasons isoperformance represents an interesting alternative to traditional methods.

Solving the Isoperformance Problem

The most important, difficult and time-consuming step in isoperformance is the approximation of the isoperformance set **I** (step 1 in Table 1, right side). In two dimensions, i.e. when we have two design variables x_1 and x_2 (n_p = n_x=2) and one performance objective J_z (n_z=1), this corresponds to mapping out isoperformance contours in two dimensions. In multiple dimensions (n_p>2) we can think of isoperformance surfaces in n_p-dimensional hyperspace. Note that a non-zero isoperformance set **I** only exists if there is "slack" in the system. This is generally the case when there are more decision variables than performance objectives (n_p>n_z) as is often the case for Engineering Systems.
One may further distinguish between **(a)** a deterministic isoperformance approach and **(b)** a stochastic isoperformance approach, see Figure 4.

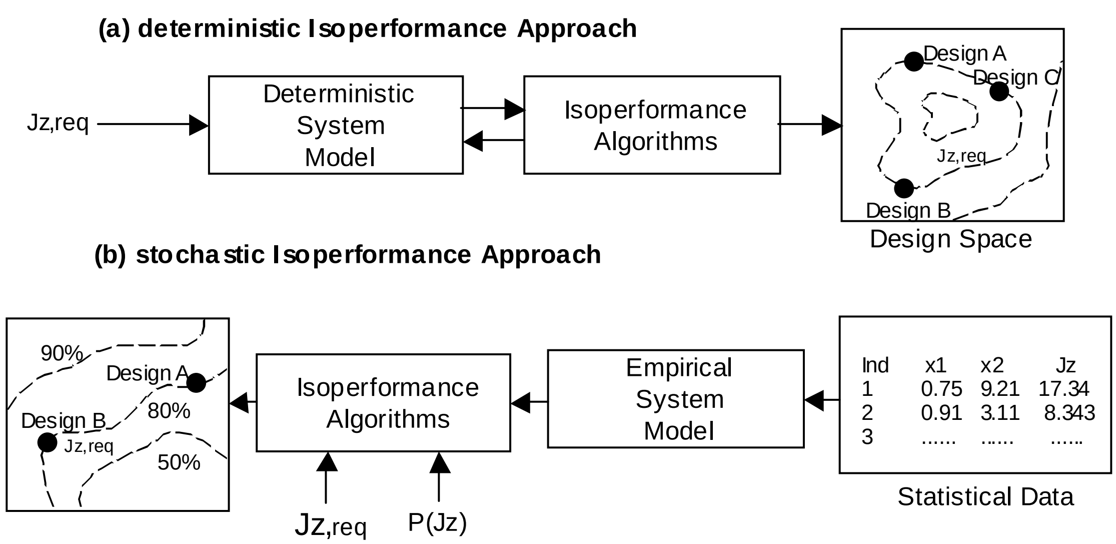


Figure 4. (a) Deterministic and **(b)** Stochastic Isoperformance Approach

In the first case the system to be designed behaves deterministically and a model of its behavior, such as described by governing differential equations $\dot{q} = A(\mathbf{x})q + B(\mathbf{x})u$ and $y = C(\mathbf{x})q + D(\mathbf{x})u$ can be obtained. Here q is the state vector, $\mathbf{x}$ are the design variables, A and B are system matrices and u are system inputs. The system response $J_z = f(y) = F(\mathbf{x})$ can then be evaluated, given inputs u and initial conditions q_o. Thus, the mapping from $\mathbf{x} \rightarrow \mathbf{J_z}$ is captured by a deterministic system model (de Weck 2002), see Figure 4(a).

Not all Engineering Systems are deterministic, particularly not those that involve human operators or natural subsystems or elements. A stochastic isoperformance approach was developed by Kennedy, Jones et al. (1990,1996,2000)[3] in the context of human factors engineering. They addressed the need within the U.S. Department of Defense to improve systems performance through better integration of men and women into military systems (human factors engineering). They present the application of isoperformance analysis in military and aerospace systems design, by trading equipment variables, training variables and user characteristics. In all these cases the relationship between decision variables and performance objectives is subject to some amount of randomness.

The stochastic approach is shown in Figure 4(b) and begins with a statistical data set from a population of "individuals" that exhibit certain attributes x_i and responses J_z. This data set is first used to create an empirical system model using regression analysis. Isoperformance contours are then extracted from such a model given a required performance level, $J_{z,req}$, and desired probability $P\left(J_z \geq J_{z,req}\right)$ that it can be achieved.

Three algorithms for finding the performance invariant set have been developed (de Weck 2002). These have been extended to the case of $n_p=n_x$ design variables and $n_z > 2$ performance metrics. Note, that an isoperformance set generally only exists if $n_p > n_z$., i.e. there are more design variables to change than performance metrics of interests. This is generally the case in complex system design. The three isoperformance algorithms are:

- **Branch-and-Bound Design Space Evaluation**
- **Tangential Front Following**
- **Progressive Vector Spline Approximation**

The interested reader is referred to reference (de Weck 2002) for details on these algorithms. Nevertheless, a particular operation from the second algorithm, tangential front following, will be discussed here, since it illuminates an interesting mathematical property of the isoperformance approach. Let ∇J_z be the system Jacobian, i.e. the matrix of partial derivatives of the n_z performance objectives with respect to the n_x design variables.

$$\nabla J_z = \begin{bmatrix} \frac{\partial J_{z,1}}{\partial x_1} & & \frac{\partial J_{z,n_z}}{\partial x_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial J_{z,1}}{\partial x_{n_x}} & & \frac{\partial J_{z,n_z}}{\partial x_{n_x}} \end{bmatrix}$$

[3] This effort lead to the founding of a consulting company called Isoperformance Inc. (http://www.isoperformance.com)

Next, assume that the Jacobian is evaluated at a point that is in the isoperformance set **I**. In order to find other performance invariant points, we need to search for the performance-invariant step directions. This is achieved by a singular value decomposition (SVD) of the system Jacobian matrix as follows

$$U\Sigma V^T = \nabla J_z^T$$

The Σ matrix contains the singular values. Here we are interested in the zero singular values. The corresponding columns of the V matrix span the nullspace of the Jacobian.

$$U = \underbrace{\begin{bmatrix} u_1 & \cdots & u_{n_z} \end{bmatrix}}_{n_z x n_z}$$

$$\Sigma = \underbrace{\begin{bmatrix} \mathrm{diag}\left(\sigma_1 & \cdots & \sigma_{n_z}\right) & 0_{n_z x (n_x - n_z)} \end{bmatrix}}_{n_z x n_x}$$

$$V = \begin{bmatrix} \underbrace{v_1 \quad \cdots \quad v_{n_z}}_{\text{column space}} & \underbrace{v_{n_z+1} \quad \cdots \quad v_{n_x}}_{\text{nullspace}} \end{bmatrix}$$

Any linear combination of these n_x-n_z vectors points in a performance invariant direction,

$$\Delta\mathbf{x} = \alpha \cdot \left(\beta_1 v_{n_{z+1}} + \ldots + \beta_{n_x - n_z} v_{n_x} \right) = \alpha V_t \beta$$

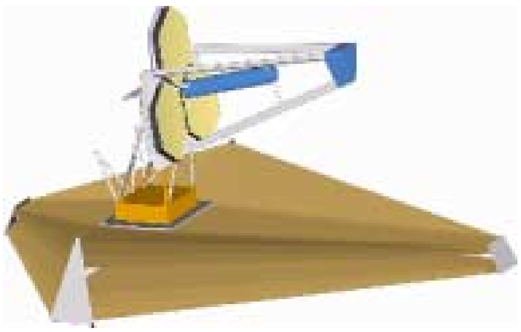
where α is an arbitrary, but small, step size and the β's are linear combination parameters. Hence, mathematically speaking, isoperformance solutions are closely related to the nullspace of the Jacobian matrix.

In this paper we are particularly interested in contours that arise, when the function J_z represents the performance of a system in a socio-technical context. Thus, J_z could represent the pointing performance of a space telescope, average range of a vehicle, total output of a power grid or the aptitude of humans as measured by some objective criterion. In economics, relationships of this type are usually called indifference curves. In sensory psychology and physiology, they are often called isofrequency, isochronal or isoelectric curves or contours. These terms all share the prefix iso-, which means "same". These contours are of value since they show the loci of "performance invariant" points in x_1, x_2-space. Graphically showing isoperformance results for n_x>3 is challenging. The next two sections provide examples of a deterministic multivariate and a stochastic bivariate isoperformance problem, respectively.

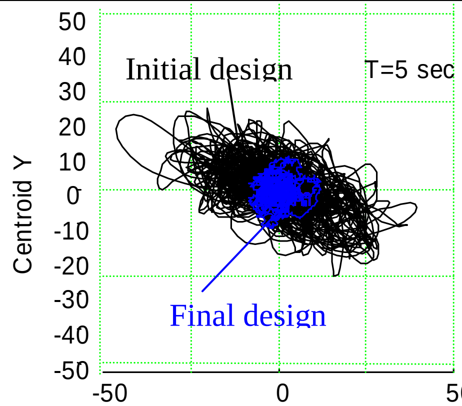
Deterministic Example (Spacecraft Opt-Mechanical Design)

The design of precision opto-mechanical systems is challenging since it combines tightly coupled disciplines such as structures, optics and controls. When applied to space telescopes such as the concept shown in Figure 5(a) we need to ensure that a high performance, i.e. (fine) pointing capability, is achieved despite the presence of various on board disturbance sources. The pointing performance measured as line-of-sight (LOS) image excursions on the focal plane can be simulated using a computer model. The results for an initial design $\mathbf{x}^{\mathbf{o}}$ are shown in Figure

5(b). The required pointing performance level of $J_{z,req}$=5 [µm] is not achieved initially as demonstrated by the excessive size of the centroid motion plot. This performance J_z is a function many design variables such as the ones shown in the Table of Figure 5(c). These 10 design variables represent the structural, optical and controls subsystems.



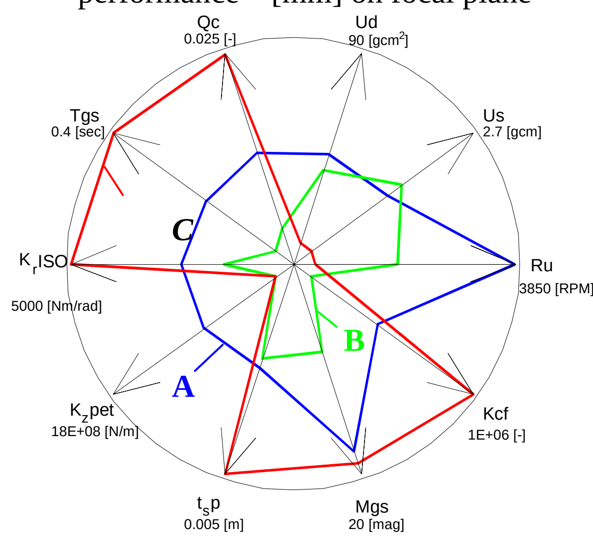
(a) Nexus Spacecraft Concept



(b) Simulation of pointing (LOS) performance – [mm] on focal plane

x_i	initial design x^o	final design "A"	units
Ru	3000	3845	[RPM]
Us	1.8	1.45	[gcm]
Ud	60	47.2	[gcm^2]
Qc	0.005	0.014	[-]
Tgs	0.040	0.196	[sec]
KrISO	3000	2546	[Nm/rad]
Kzpet	0.9E+8	8.9E+8	[N/m]
tsp	0.003	0.003	[m]
Mgs	15	18.6	[Mag]
Kcf	2E+3	4.7E+5	[-]

(c) Table of Nexus design variables[4]



(d) Radar plot of three performance-invariant designs

Figure 5: Isoperformance results for Nexus Spacecraft Design

An isoperformance analysis according to Table 1 (right side) was conducted and the results are shown in the radar plot of Figure 5(d). The plot shows three designs A,B, and C, that all achieve the same required pointing performance of $J_{z,req}$=5 [µm]. The radar plots seem to indicate that this performance is achieved in different ways. Design A is the design that is the most "balanced". On average this design allows all design variables x_i to remain as close as possible to

[4] These design variables represent Ru=upper reaction wheel speed, Us=static wheel imbalance, Ud=dynamic wheel imbalance, Qc=cryocooler attenuation factor, Tgs=guidestar sampling rate, KrISO= Isolator stiffness, Kzpet=mirror petal mount stiffness, tsp= secondary mirror spider wall thickness, Mgs=guide star magnitude, Kcf=Optical fine pointing controller gain.

the mid-range between their bounds $x_{i,LB}$ and $x_{i,UB}$. Design B is the design that achieves the performance with the smallest control gain K_{cf}. Presumably this is the lowest energy design. Finally, design C is the design that exhibits the smallest uncertainty (+/- 5.3%) in the nominal performance prediction. This is achieved by sharply reducing the magnitude of the disturbance noise, which is the largest source of uncertainty. For brevity we chose design A as our final design and show the values of the design variables in the third column of Figure 5(c).

A verification that the design meets the performance requirements is shown by the smaller, lighter trace in Figure 5(b). This level of clarity and physical insight would not have been obtained from a pure "black box" optimization approach. Design A meets the performance requirements and is neither grossly over- or underdesigned. Furthermore the burden for achieving the performance has been "evenly" distributed in the system instead of pushing a single subsystem to its expensive bounds. This is a reflection of the author's belief that good system design practice should search for balanced, acceptable rather that point-optimized designs that give rise to many active constraints.

Stochastic Example (Human Factors "Design")

Many complex Engineering Systems interact with human operators whose abilities have been traditionally investigated in applied psychology and human factors engineering. This leads to a probabilistic view of the isoperformance approach, where contours of equal performance are obtained from empirical models of the form

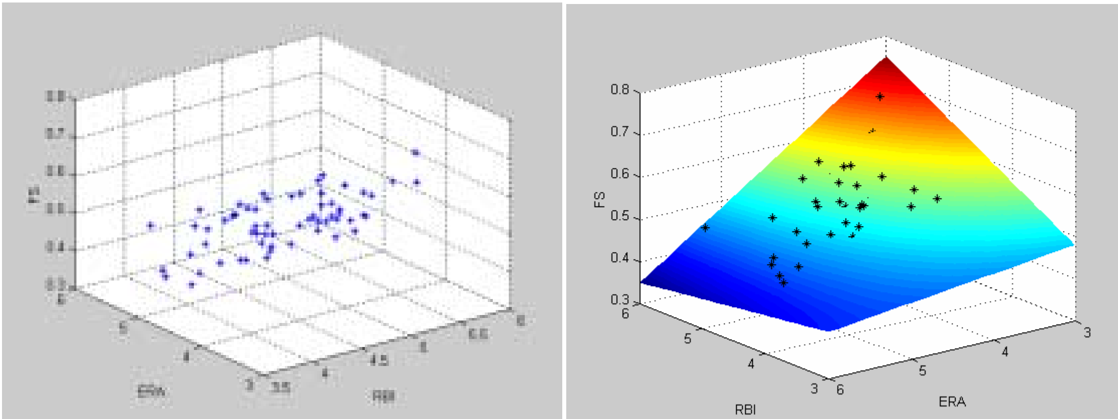
$$E\left[J_i\right] = a_0 + a_1\left(x_{1,i}\right) + a_2\left(x_{2,i}\right) + a_{12}\left(x_{1,i} - \overline{x_1}\right)\left(x_{2,i} - \overline{x_2}\right) + \ldots$$

where E[ ] is the expectation operator, J_i is the performance of the i-th individual or system, a_o-a_{12} are fitting parameters, $x_{1,i}$ and $x_{2,i}$ are design variables or characteristics and $\overline{x_1}, \overline{x_2}$ are the mean values of a given data set. Kennedy and Jones (1996) have discussed the problem of finding the isoperformance curve of a baseball team in terms of its final standings (*FS*=games won/total number of games) as a function of the team's batting ability (RBI-runs batted in) and pitching ability (ERA-earned runs average)[5]. They argue that RBI and ERA can be viewed as independent variables, since the players responsible for achieving these statistics are usually not the same. Teams with high final standings (>500) are expected to have both good pitching and batting, but for any realistic desired final standing it would be desirable to obtain the tradeoff curve between the two factors. The first step is to compile the statistical data and to fit an empirical model to it. In multidisciplinary design optimization this is sometimes called a response surface. The empirical model in the baseball example becomes

$$E\left[FS_i\right] = a_o + a_1\left(RBI_i\right) + a_2\left(ERA_i\right) + a_{12}\left(RBI_i - \overline{RBI}\right)\left(ERA_i - \overline{ERA}\right)$$

The fitting parameters are obtained by compiling the ERA, RBI and FS standings from past seasons[6] and fitting a response surface or empirical model in a least-mean-squares sense. The original data and fitted empirical model are shown in Figure 6, respectively.

[5] The third major category are the fielding statistics, which are ignored here.
[6] The 2000 and 2001 major league baseball (MLB) results are used here (60 data points = 2 seasons x 30 teams).



(a) (b)

Figure 6: (a) Raw statistical data for 30 teams and 2000, 2001 seasons in terms of ERA, RBI and FS. (b) Fitted empirical model with a_o=0.7450, a_1=0.0321, a_2=-0.0869, a_{12}= -0.0369. The standard deviation error of the empirical fit is $\sigma_e = 0.0493$.

The second step is to determine the expected level of performance for team *i* such that the probability of adequate performance is equal to the specified confidence level. We can write

$$E[J_i] = J_{req} + z\sigma_\varepsilon$$

where E[J_i] is the expected level of performance of team i, J_{req} is the desired (required) final standing at the end of the season, z is the confidence level obtained from a normal distribution lookup table of the Gaussian distribution function

$$\Phi(z) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{z} e^{-\frac{z^2}{2}} dz$$

and σ_e is the aforementioned fitting error. This assumes that the error for the empirical model follows a normal distribution. Now let the decision maker (e.g. team owner "i") decide that the required final standing should be FS_i=0.550 and that the probability that this result (performance) should be achieved is 80%. Then we obtain the expected (target) final standing as

$$E[FS_i] = .550 + z\sigma_r = .550 + 0.84(0.0493) = 0.5914$$

In other words, if the final standing FS of team *i* is to equal or exceed .550 with a probability of .80, then the expected final standing for team i must equal 0.5914. Finally the isoperformance contour for this desired performance can be obtained analytically or with one of the algorithms from [3] as

$$RBI_i = \frac{.5914 - a_o - a_1 ERA_i + a_{12}\overline{RBI}\left(ERA_i - \overline{ERA}\right)}{a_1 + a_{12}\left(ERA_i - \overline{ERA}\right)}$$

The isoperformance curves for the baseball example are shown in Figure 7. Some interesting conclusions can be drawn. The contour seems to suggest that the desired final standing could be achieved with an excellent pitching staff (ERA=3.0) and modest batting staff (RBI=4.2) or conversely with a stellar batting staff and lesser pitching staff (RBI=6.0 and ERA=4.2).

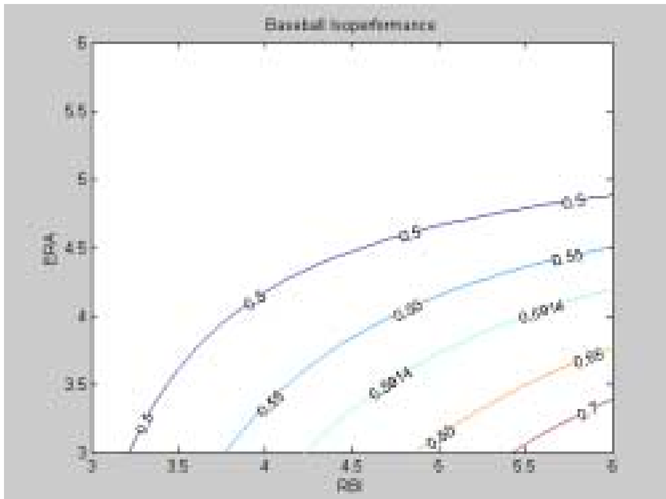


Figure 7: Isoperformance curves in terms of final standings (*FS*) for stochastic example

This tradeoff curve could be used by a team owner for resource allocation and "team design" purposes. It is interesting to see that the performance FS seems to be more sensitive to changes in pitching performance (ERA) than batting performance which seems to support the commonly held view that good pitching is most important in major league baseball. Also, as the performance requirement (*FS*) becomes more and more ambitious, the number of options or length of isoperformance contour becomes smaller.

Conclusions and Recommendations

It is often true that traditional engineering education and practice makes heavy use of system optimization. Optimization is, of course, an important method and spawns a number of algorithms (numerical gradient search, heuristic techniques like genetic algorithms and simulated annealing) designed to maximize or minimize certain system responses. In reality, however, the notion of optimality for large, complex systems is somewhat less clear. In the case of multiple objectives we may consider Pareto-optimality. This paper argues that traditional optimization of system performance is not the only reasonable approach in the design and analysis of complex systems. Isoperformance, an alternative approach, does not seek the extremes of system performance, but enforces that the system meets pre-determined performance targets (=requirements). This insures that the system is neither over nor under-designed. What can be gained by this approach?

Three potential benefits arise from using the isoperformance approach:

(1) Considers not just a single, “optimal” point design but a family of performance-invariant, but Pareto-optimal designs in terms of their cost and risk.

(2) Designs can be found, within the performance invariant set, such that the burden for achieving the system performance is well “balanced” among subsystems.

(3) Offers greater insights into the inherent tradeoffs between performance, risk and cost and allows the system analyst or designer to be more interactive

Let us conclude with the remark that we should consider **performance as a surrogate “currency” for complex systems that are composed of technical and human elements.** The fact that sub-optimal system performance is acceptable allows considering the difference between the “optimal” performance and the lesser, required performance along the isoperformance contours as a resource. This performance margin can be viewed as a “currency” that can be invested in different ways: making the system more affordable to implement, more robust or flexible, easier to upgrade in the future … This notion enables a connection between system performance, optimization and lifecycle properties of complex systems.

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Biographies

Olivier L. de Weck is currently an assistant professor with a dual appointment between the Department of Aeronautics and Astronautics and the Engineering Systems Division (ESD) at MIT. His research interests are in Integrated Modeling and Simulation, Multidisciplinary Design Optimization and System Architecture. In 2001 he obtained a Ph.D. in Aerospace Systems from MIT. From 1987 to 1993 he attended the Swiss Federal Institute of Technology (ETH Zurich) in Switzerland, where he earned a Diplom Ingenieur degree (MS equivalent) in industrial engineering. From 1993 to 1997 he served as liaison engineer and later as engineering program manager for the Swiss F/A-18 program at McDonnell Douglas (now Boeing) in St. Louis, MO. Since 2002 he is a member of the AIAA Multidisciplinary Design Optimization (MDO) Technical Committee (TC).

Marshall B. Jones is professor emeritus of Behavioral Science at The Pennsylvania State University and was for 24 years chairman of that department in the College of Medicine. He has conducted extensive research in human factors, psychiatric genetics, especially the genetics of autism, the spread of attitudes and behaviors from one person to another, and the prevention of antisocial behavior. He currently serves as board chairman of Keystone Human Services, a large behavioral health organization headquartered in Central Pennsylvania but active in Connecticut, Maryland, Delaware, and, recently in Eastern Europe, as well as in Pennsylvania. Jones received his B.A. degree from Yale in 1949 and his Ph.D. from the University of California at Los Angeles in 1953.