Advances in Mechanical Systems Synthesis

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Abstract

The objective of current research is to provide dynamic evaluation of design performance during system synthesis. Initial efforts focused on the development of object oriented CAD systems wherein design features encapsulated the necessary performance behaviors. The most recent research is directly investigating systems-level synthesis and performance evaluation on three fronts. First, component consolidation guidelines for injection molded products have been developed from fundamental cost models. Second, a method for maximizing system flexibility has been developed for design environments with variation and uncertainty. Third, a design representation has been invented that resolves and facilitates system-level constraint management.

Introduction

"The goal of 'intelligent' computer-aided-design (CAD) systems is to provide greater support for the process of design, as distinguished from drafting and analysis. More supportive design systems should provide a quick and simple means of creating and modifying design configurations, automating evaluation procedures (e.g. manufacturing), and automating interfaces to analysis procedures." [1] This quote indicates an accepted view of the design process which the majority of related research has pursued. The goal is inadequate given the competitive pressure in modern product development projects and the current interdisciplinary role of design engineers. Rather, the long-term vision of this research is to integrate analysis within the process of design thereby automating many evaluation procedures and enabling parallel design development and understanding of design behavior.

Towards this objective, our initial research investigated the possibility of encapsulating the design performance behaviors within the feature representation of object oriented CAD systems. However, two major insights reduced the vitality of this initial approach. While performance was successfully predicted in pure feature-based design prototype environments, we recognized that the definition and analysis of generalized form features was practically

infeasible. This generalization would require the consistent formation of specifications, topology, boundary conditions, and analysis methods from arbitrary surface geometries – an effort which we did not wish to pursue. Second, we recognized the elegance and power of the discretization-based analysis methods. The derivation and management of discrete elements has been largely solved. Moreover, ever-increasing computing power will eventually provide the feasible use of this method with design environments. As such, our feature-based analysis efforts have been discontinued.

The primary focus of our research has been the dynamic evaluation of system-level performance during the product development process. The research has led to contributions on three significant and complimentary fronts. The potential impact of the results is significant. In academia, students should gain more robust and theoretical understanding, engineering intuition, and confidence by exploring analysis in the context of design synthesis. In industry, designers should synthesize more robust designs in reduced product development times.

Component Consolidation

Overview: Complex systems are known to consist of finite variety of interacting elements. According to Scurcini the number, variety, types, and the organization of elementary components drive the complexity of a technological system [2]. Since form and shape features constitute the basic components of a plastic part, an enumeration of the features in a designed part could be functionally related to its complexity. Part complexity together with other mold cost drivers can then be used to determine its tooling cost, etc.

Injection molding form features were classified as shown in Figure 1 to conform to the Form Feature Information Model (FFIM) established for the Standard for the Exchange of Product Data (STEP) [3]. However, cost estimation models built on a fixed number of features are soon rendered obsolete since the designer has the freedom to define application-type features. In our research, the initial approach was to assign every type of feature a price tag based on the cost or difficulty of reproducing the feature in an injection molded part. A process to count parts' features from blueprints was initiated. However, correctly identifying and classifying all the geometrical features of a part from its blueprints or even from a physical sample is not a trivial task. Two engineers could correctly prepare different feature lists given the same part.



Figure 1: A Classification of Injection Molding Features

For the purpose of cost estimating, however, we only need to know the complexity created by the number and variety of features. We surmised that the number of dimensions that are used to define a feature is a measure of its complexity since the more dimensions that are used to define a feature, the more difficult it is to manufacture the feature. Every dimension represents an additional point to check or a setup to make in the manufacturing of the mold. This reasoning is then logically extended to the total number of dimensions required to completely define the parts' model. This is particularly true in constraint-based modelers, which include most 3-D CAD systems, where for example a solid block would require three dimensions (height, width, and thickness) to be uniquely defined.

Cost Modeling: A custom injection molder in Western Massachusetts assisted in this research. Original equipment manufacturers (OEM) submit requests for quotes (RFQ) to this company. The company in turn sends out requests for tooling quotes to moldmakers locally and overseas. Seventy-five mold tooling quotes of single cavity molds for thirty of the parts that the company has quoted in the past three years were selected for analysis from its records. According to the tooling engineer at the custom molder, past performance is a critical factor they considered in giving out tooling contracts to moldmakers. The size of the part, its complexity, number of slides, gate type, surface finish, injection and ejection systems, are some of the factors that are considered in the rough estimation of a part's tooling.

Multiple regression analyses were performed with the mean mold quotes and mean lead-times as dependent variables. Other parts attributes measurable from a blueprint or CAD model were examined, such as part projected area, material volume of part, number of critical-to-function dimensions, variety of dimensioning and tolerancing annotation. The resulting cost model had a correlation coefficient of 0.91. The resulting lead time model had a correlation coefficient of 0.91. The resulting lead time model had a correlation coefficient of 0.71. The imperfect correlation may be due to other molder specific factors, such as availability of excess capacity, or willingness to expedite a job to gain a customer.

The results estimate the effects of increases in complexity, as measured by the number of dimensions, on tooling cost and tooling lead-time compared to the effects of size increases. To be specific, a 100-count increase in the number of dimensions, which is a normal phenomenon when parts are consolidated into complex parts, increases tooling cost by \$3000, and tooling lead-time by 5 days. A comparable increase in mold cost due to size increase is only possible if the size of the part is increased by 5,600 cc, a six-fold increase if starting with a 1000 cc part.

Problem Definition: Suppose there are n separate parts to be consolidated into m parts, m less than n. As parts are combined, assembly cost is reduced. The consolidated parts are, however, larger and more complex. Our goal in this research was to establish if total component consolidation in complex mechanical assemblies is always beneficial. If not, we should determine the conditions under which component consolidation is undesirable. The

domain of plastic parts is especially applicable to this investigation as the injection molding process enables the manufacture of very complex parts at seemingly low marginal costs.

While cost models can and will be used directly for numerical optimization and comparison of design alternatives, it is useful to investigate the generic behavior of the component consolidation problem. Consider the common objective function to maximize profit in product development:

$$\max \Phi = V \cdot (P - C) \tag{1}$$

where profit is defined as the sales volume, V, multiplied by the sales price, P, minus unit cost, C. To consider the effect of component consolidation and complexity on profit, the partial derivative of profit with respect to complexity, K, may be applied to seek for minima and maxima:

$$\frac{\partial \Phi}{\partial \mathbf{K}} = \frac{\partial V}{\partial \mathbf{K}} \left(P - C \right) + V \left(\frac{\partial P}{\partial \mathbf{K}} - \frac{\partial C}{\partial \mathbf{K}} \right).$$
(2)

Since the relations from complexity to volume, price, and cost are difficult to determine directly, the appropriate chain rules may be applied. For instance, volume is a function of time to market which itself is a function of tooling complexity. Similarly, unit marginal cost is the sum of direct material cost, processing cost, ammortized tooling cost, and assembly costs – all of these subcosts are functions of complexity. Applying the appropriate chain rules for dependent variables leads to the following equation:

$$\frac{\partial \Phi}{\partial \mathbf{K}} = \left(P - C\right) \left(\frac{\partial V}{\partial T} \frac{\partial T}{\partial \mathbf{K}} + \frac{\partial V}{\partial S} \frac{\partial S}{\partial \mathbf{K}} \right) + V$$

$$\left(\frac{\partial \Phi}{\partial \mathbf{K}} - \left(\frac{\partial C}{\partial C_{mat}} \frac{\partial C_{mat}}{\partial \mathbf{K}} + \frac{\partial C}{\partial C_{proc}} \frac{\partial C_{proc}}{\partial \mathbf{K}} + \frac{\partial C}{\partial C_{proc}} \frac{\partial C_{proc}}{\partial \mathbf{K}} + \frac{\partial C}{\partial C_{assy}} \frac{\partial C_{assy}}{\partial \mathbf{K}} \right) \right)$$

$$(3)$$

Inspection can now be used to eliminate terms from the above equation. The sales volume potential, S, is not a function of complexity and thus the partial derivative is zero. The unit sales price, P, is also not considered to be function of complexity though this can be debated due to the potential effects that component consolidation has on product functionality, performance, failure, or warranty costs. The resulting simplified model for profit consolidation states:

$$\frac{\partial \Phi}{\partial K} = \underbrace{\left(P - C\right) \left(\frac{\partial V}{\partial T} \frac{\partial T}{\partial K}\right)}_{Processing Costs} - \underbrace{\left(\frac{\partial C_{mat}}{\partial K} + \frac{\partial C_{proc}}{\partial K} + \frac{\partial C_{assy}}{\partial K}\right)}_{Processing Costs} - \underbrace{\left(\frac{\partial C_{mat}}{\partial K} + \frac{\partial C_{proc}}{\partial K} + \frac{\partial C_{assy}}{\partial K}\right)}_{QK} - \underbrace{\left(\frac{\partial C_{tool}}{\partial K} + \frac{\partial C_{tool}}{\partial K}\right)}_{QK} - \underbrace{\left(\frac{\partial C_{tool}}{\partial K} +$$

This model will generate both obvious and surprising insights, though some discussion regarding differential calculus is first warranted [4]. Consider, for example, the parabola $y=-x^2$ or any simple analytic function. It is well known that a local maxima will occur at a point where the magnitude of the first derivative switches from positive to negative. Since the design complexity is a positively ranged value, any term lending a positive value to profit sensitivity will justify greater levels of design complexity. Similarly, reduced design complexity is driven by terms lending a negative value to the profit sensitivity.

Discussion: Each of the three terms in (6) will tend to drive the design to a different level of component consolidation. The first term represents the real cost of lost sales due to extended product development times as the component consolidation and complexity increases. Two results are fairly clear from this first term. First, a product with an infinite life cycle would have no sales loss with increase in development time, i.e. $\partial V/\partial T$ is zero. Ignoring functionality and warranty issues, this effect will drive the design towards total component consolidation and maximal complexity. Second, greater consolidation is also desired if development time is not sensitive to design complexity. As these two differentials increase, however, less component consolidation may become optimal. It is also noted that optimal complexity is a function of the unit profit margin, price minus cost. Since the term $\partial V/\partial K$ is normally negative, higher profit margins "raise the ante" thus increasing the importance of time to market and give reason for reduced component consolidation.

The second term represents the sensitivity of unit processing cost to design complexity. This derivative function is neither linear nor monotonic. As components are consolidated into a single more complex component, the direct material costs will tend to decrease. This behavior is due to the elimination of interface material, such as redundant side walls between two joined boxes, as well as the elimination of fasteners such as snap fits, screws, etc. Similarly, the assembly costs will tend to decrease with component consolidation due to a reduced number and simplification of assembly operations. However, the processing costs will tend to rise with design complexity for several reasons. Component consolidation frequently results in fewer larger parts, which if injection molded require greater injection pressures and clamp tonnages. Moreover, greater design complexity not only commands additional requirements but also that the process be maintained to produce the most critical required tolerance. Thus, the optimal level of component consolidation is dependent on the application characteristics and manufacturing process capability.

Finally, it should be noted from the second term that higher production volumes, *V*, will tend support higher levels of component consolidation when the net sensitivity of unit processing cost to design complexity is negative.

The third term, tooling cost sensitivity, indicates the savings in tooling costs that may be achieved with component consolidation. At first, the term 'savings' may be considered controversial, as it is well known that tooling costs increase with increasing design complexity. However, the results of the model development, e.g. equations (1) and (2), indicates that the cost intercept for a mold with zero complexity is approximately \$25,000. Since the cost per added dimension is approximately \$50, the field research indicates that (from a tooling cost standpoint) it is almost always desirable to consolidate mold tooling. The exceptions occur in uncommon circumstances: for instance, when two parts are joined and the resulting volume envelope is significantly larger than the sum of the two part volumes, or when the joining results in a significant increase in the tolerance, surface finish, or mold actuation. The tooling cost sensitivity will thus generally, but not always, indicate a tendency towards increased component consolidation.

Results: To investigate the effect of component consolidation in a complex application, this analysis was applied to an internal chassis of an office automation product shown in Figure 2. In this design, a very complex component consisting of approximately 1,000 features and twenty critical dimensions was deconstructed into six sub-components. The six components were then re-integrated in every feasible combination, resulting in forty-two alternative component designs. Finally, the forty-two subcomponents were reassembled in eighty feasible combinations to provide the functionality of the original product.



Figure 2: Internal Chassis Designs

The resulting marginal cost for the assembled product as a function of component consolidation level is shown in Figure 3. As previously stated, the product's marginal costs will generally decrease with increasing component consolidation and component complexity. This is due to the linear nature of the cost models in which there is an intercept cost of \$25,000 is devoted to each mold plus an additional cost per unit of complexity. Since the total product complexity remains approximately the same independent of number of components (features are shifted to/from molds but not generally eliminated), the number of molds drives the tooling costs up. As such, the minimal marginal cost occurs with the original design of the product in which all sub-components are integrated into one complex component.



Figure 3: Product Marginal Cost vs. Component Consolidation

Total consolidation may not always result in the lowest product costs. Reviewing equation (6), there are two primary factors that justify reduced component consolidation: 1) sales cost, $\partial V/\partial K$, and 2) processing cost, $\partial C_{proc}/\partial K$. If the manufacturing process capability is poor, then the yield fraction of acceptable parts will quickly degrade as the number of quality requirements increases with component complexity. If the process capability index, C_P , reduces from 1.0 (p_i =0.997) as assumed in Figure 3 to 0.25 (p_i =0.933), then the marginal cost distribution shown in Figure 4 results. In this case, the optimal configuration is not total integration but rather separating the integrated component into three components of different sizes with approximately equal complexity.



Figure 4: Product Marginal Cost for Low Process Capability

Since a product with multiple tools is dominated by the longest tooling time, the total tooling time will be dominated by the production of the maximum complexity component. Designers generally desire few components in a product to lower assembly costs but also low complexity of the components to shorten time to market.

This trade-off in design complexity is explicitly shown in Figure 5, which plots the product marginal cost against the tooling development time. The Pareto optimal curve may be superimposed and the solution is found according to the time:price sensitivty line. In Figure 5, the dark curve is the Pareto boundary – all space to the left and bottom of this curve is infeasible for this system. The other lines represent market sensitivities. The dashed line represents a market that has long life cycles, i.e. $\partial V/\partial K$ equals 0. In this case, low marginal costs and long lead times are justified due to insignificant costs of lost sales. At the other extreme, short life cycle products (dotted line) will incur extreme penalty costs so that lower complexity is desired. The third solid line shows an intermediate sensitivity. As such, multiple optimal configurations may exist dependent on the market dynamics. The development team should consider the market and processing costs when selecting component consolidation strategies.



Figure 5: Product Delays vs. Product Marginal Cost

The optimal configuration for a given product depends significantly on the application characteristics such as form, complexity, tolerance, profit margin, assembly cost, production volume, and life cycle. DFMA states that components should always be combined except when [5]:

- the components move relative to each other,
- the components need to be of different materials,
- the components need to be separable for assembly or disassembly...

...to which additional guidelines can be provided:

- the consolidation does not reduce the number of tools,
- the components have vastly different quality requirements,
- the design process is not certain of delivering the product and there is significant sales cost sensitivity, and
- the manufacturing processes are not capable of delivering high yields of complex products.

Risk Management

The robust engineering design process is used to create an economic design robust against noise using models, simulations, and previous experience. This robust design approach is widely used in research and is in the process of adaptation in the industry. However, these robust design approaches usually assume correct performance predictions using models and simulations. Yet, those models and simulations are not always perfectly accurate. Assumptions are frequently made while creating and using those models and simulations. If one or more of those assumptions are incorrect or not precise, the predicted design performance may differ from the actual design performance. Depending on the sensitivity of the design this may cause defects because the actual design responses differ from the predicted design response. In order to improve the design, changes have to be made, delaying the development process and increasing the development cost.

The current research aims to increase the design robustness to include variations in the prediction models and simulations in order to create a fail-safe design. This is possible by including uncertainty variations of the predictions into the robust design model in order to reduce the probability of a design change. This robustness against uncertainty solutions is described in more detail in the third section of this overview. Unfortunately, this increased robustness including not only noise but also uncertainty comes frequently at an increased cost of the design. However, the robustness against uncertainty is needed only to include a one time offset due to uncertainty, which could be adjusted for at a later stage of the design. While it is not possible to adjust for noise, which is different for each item produced, it is possible to adjust for prediction errors, which are constant for a selected design. Therefore, the increased robustness against uncertainty is needed only once for the creation of the design, but this may increase the cost for every produced item.

To overcome this problem, research is undertaken to create a flexible design which is economic, yet in the case of defects due to uncertainty can be changed by adjusting only certain design variables which are easy to change. While some design variables are very costly to change and cause significant delay, other design variables can be changed in a very short time at a very small cost. This research aims to create economic designs robust to noise, yet with the ability to change with only a small change effort in time and cost.

Design for Variation: The method of robust design is standard knowledge in the engineering research community, and many variations have been developed [6-11]. One variation described below is used within this research for the additional methodologies of design robust against uncertainty and flexible design.

A Basic element of most robust design approaches is the prediction of the design response with a mean and a variation based on the design variable mean and variation using prediction models and simulations. The goal is to position the mean response in a safe distance of the specification limits based on the width of the distribution in order to minimize the probability of a defect as shown below.



Figure 6: Variation Distributions

Within this approach, the probability of a specification satisfaction can be determined by integrating the response distribution between the lower and upper specification limit as:

$$P_{i} = \int_{LSL_{i}}^{USL_{i}} pdf(y_{i})$$

$$P = \prod_{i=1}^{n} P_{i}$$
(5)

The joint probability of satisfying all specifications is the product of the probability of satisfying the single specifications as shown above, assuming no interactions. In this robust design optimization approach, the quality of the design is measured monetary, including the cost due to defect parts. Using standard cost estimation, the marginal part cost C^{MP} is determined. In addition, the yields for the design responses are evaluated. Next, the percentage of design defects has to be integrated into the total part cost. A conservative approach is to assume the creation of a marginal cost for each defect part. If for example the total yield is 50%, two parts have to be produced in order to receive one good part. Therefore, the total cost C^T for the satisfying part cost sists of the marginal cost of two parts, the satisfying part, and the defect part. A general evaluation of the total part cost using this approach can be done by dividing the marginal part cost C^{MP} by the yield, i.e. the joint probability of success *P* as shown below. This cost is then minimized to generate the optimal robust design as shown below.

$$C^{T} = \frac{C^{MP}}{P}$$

min *s.t*.

$$C^{T,i}$$

$$LSL_{y_i} \le y \le USL_{y_i} \quad \forall i$$
(6)

Design for Uncertainty: The method described above, however, assumes correct prediction models. However, if those models are inaccurate, the predicted responses may differ from the actual responses, causing additional defects. The fail-safe robust design therefore includes both noise and prediction uncertainty into the response evaluation. Within this methodology, the response uncertainty is also assumed as a statistical distribution. This

distribution can be evaluated by comparing the predicted responses with the actual responses of multiple previous designs. The model is visualized in the figure below, where an input distribution $pdf_N(x)$ causes a distributed response pdf(y) according to a functional relation y=g(x). However, this functional relation is also distributed by $pdf_U(y^U)$ and causes additional variation in the design response.



Figure 7: Uncertainty Distributions

These probability density distribution $pdf_U(y^U)$ of the response uncertainty y^U and the distributions due to noise $pdf_N(y^N)$ and $pdf_N(x)$ are included in the evaluation of the combined probability density distribution $pdf_{II}(y)$ as shown below. Using this robustness definition, it is possible to improve the design with respect to the noise and prediction uncertainty, improving the probability of a feasible design.

$$y = g(x_1, x_2, ..., x_m, y^N, y^U)$$

$$pdf_{II}(y) = h(pdf_N(x_1), pdf_N(x_2),$$

$$..., pdf_N(x_m), pdf_N(y^N), pdf_U(y^U))$$
(7)

Based on this robustness definition, the design is optimized to minimize the total cost including the defect cost as described in the previous section. A more detailed description is available [12].

Flexible Design: The flexible design approach aims to create an economic design robust against noise. However, at the same time the design should be flexible enough to be changed with little effort in case the prediction uncertainty causes defects. The flexibility of different designs is compared with each other, and the design with the best combination of economic design and flexible design is selected.

To evaluate the flexibility of a design, the combinations of design changes have to be analyzed. The table below shows an overview of the comparison of different design changes. In the first case, no changes are performed. This design has a low cost using a standard robustness definition. However, this design also has a high cost using a fail-

safe robust definition. By changing variable A and optimizing for the fail safe robust cost, this cost can be decreased, however, this will cause an increase in the standard robust cost. Similar effects of varying magnitude can be seen for other design changes with different variable combinations. In addition, the change cost for each variable combination is determined.

Α	В	С	Standard Robustness	Fail Safe Robustness	Change Cost	Comment	
			Total Cost	Total Cost	per Part		
-	-	-	4.00	6.00	0.00	No Changes	
-	-	+	4.50	5.50	0.30	Change A	
-	+	-	4.30	5.90	0.15	Change B	
-	+	+	4.60	5.45	0.30	Change A&B	
+	-	-	4.20	5.50	1.20	Change C	

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By investigating this table, it can be determined how much the fail-safe robustness can be improved by investing a certain design change effort. Based on this investigation it is now possible to compare different designs not only using the standard robust cost or the fail-safe robust cost, but also by the flexibility with which a design can be changed. There is currently research in progress investigating and describing the design flexibility comparison methodology in greater detail.

Further Research: The methodologies described above can be used to minimize the probability of a design change, therefore reducing the time and cost required for a changing a design. In addition, design flexibility aspects are currently under research, and the investigated approach is described above in more detail. Using this approach, it will be possible to minimize the overall expected cost of the design including the design development cost. The time required for design changes can also be estimated, and depending on the trade off between time and cost is included in the optimization criteria. Therefore, this approach also considers the development process with the associated cost and time in the optimization criteria's in an effort to represent the holistic view of the design and the design development process.

Performance Modeling

Engineering and manufacturing is the largest single economic activity in modern society. Under the pressure of high competition, the engineers have turned to computer-aided systems to assist them in the task of product design and manufacturing. While the technology like Computer Aided Design (CAD) has significantly improved the productivity and the quality of the design, there is a widespread view that CAD is not yet adequate as an aid to the designer in generating a design [13-15]. Most CAD tools of today focus too much on providing a means of representing the final form of the design, whereas designers also need a continual stream of information and analysis

to assistant throughout the engineering design process, especially in the early stages when the detailed form of the product is vague.

While it is well recognized that engineering design is an unstructured but logic-based process where successive iterations of synthesis and analysis eventually converge to the desired solution [16], there are increasing concerns about engineering design as a decision-making process [17]. In this case, the objective of the design representation is to decide what the right design candidate/candidates is and how to reach this solution among different design possibilities. Since the simple enumeration of various alternatives and their combinations will lead the design to lengthy or infinite iteration, the representation for decision-based design should be not only geometrically descriptive but also functionally predictive. While descriptive models depict the existence of the reality and can be justified by trivially comparing the model with the facts, predictive models, however, need more deliberate validation due to uncertainty in the engineering design, which result from the unperfected model itself and external variation.

One problem that engineers face is the role of creativity in the design process [18]. It is very difficult, if not impossible, to model the creative design synthesis. As current knowledge on artificial intelligence is far away from maturity, the design model can not and should not exclude the interaction with the designer. Rather, a good design representation should provide the synchronization mechanism to dynamically represent the modified design.

Design representation has been acknowledged as one of the greatest problems in design research. The representation is fundamental to the whole development process. The objective of this research is to explore a solid design representation in order to improve the design quality and reduce the lead-time in the iteration of engineering design. As a practical design model, the representation tends to utilize the power of computer-aided techniques and facilitate the development of existing and future design methodologies, such as axiomatic design, robust design and conceptual design. It is our belief that the establishment of such a representation will eventually enable intelligent assistance for product development.

Performance Orientation Chart: The performance-based representation builds the relationships between performance attributes and design parameters in order to visually guide the design process. The Performance Orientation Chart (POC) is the core of the representation. While the POC is similar with the House of Quality (HOQ) in structure, the content is very different. The HOQ focuses on deriving the engineering specifications from the raw customer requirements qualitatively, whereas the POC analyzes the relationship between the required specifications and the design parameters quantitatively. There are seven parts in the POC as shown in Figure 8. The designer starts with performance attributes **1** and design parameters **2**. While it is another active research area how to get the clarified design variables [15, 19, 20], the POC assumes that the design will be hierarchically structured well. The design form **3** graphically represents the design relationship between design parameters x_i and performance

attributes y_j . While the concept of the design form is not new, the POC offers two other regions – the constraint parameter space **4** and the feasible performance space **5**, which are respectively made up of the cells x_j vs. x_j and y_i vs. y_i . Finally, the assessments **6** and **7** of design parameters and performance attributes provide another way to cross check our thinking and uncover gaps in engineering judgment [21].



Figure 8: Performance Orientation Chart

Based on the principles described above, the research is focusing on implementing the POC in the linear problem (LP). The linear problem is adopted because its simplicity make possible to have a truthful insight for the POC. At the same time, the popularity of LP ensures the POC the practical significance. It is also noted that the POC is distinguished from the traditional linear optimization problem that looks for the min/max goal. Instead of the stable objective function in the LP (either one performance attribute or the combination function of multiple attributes), the engineering design is difficult to find such an explicit function, especially at the early stages of the design process. As such, the POC is proposed to gather the understanding throughout the design process. Figure 2 shows the design form, the constraint parameter space and the feasible performance space of the POC for a linear problem.

Design Form: The design form is a graphical representation of the relationship between performance attributes, y_i , and design parameters, x_j . The performance y_i can be stated as:

$$y_i = f_i(x_1, x_2, ..., x_j, ...) \quad \forall i, j$$
 (8)

Here $f_i(X)$ is the measuring function of the performance attribute for a set of design variables, $X = (x_1, x_2, ..., x_j, ...)$. The function may involve one or more design parameters. With the simulation or engineering measuring function, the intersection cell between the performance y_i and the design parameter x_j can be stated as $y_i = f_i(x_j)$ where the other design parameters are substituted by the current constant value. Therefore, a graphical matrix can be plotted for all

intersection cells of the POC. The dynamically updated graph will lead the designer through the iterative design process until the satisfied solution is found.

While the design form occasionally helps the designer explicitly understanding the relationship between design parameters and performance attributes, it is also very likely for the designer to lose the way in the maze of design variables. The constraint parameter space and feasible performance space intend to further the assistance by explicating the intricate correlations inside the design parameters and the performance attributes.

Parameter Constraint Space: The engineering design can be described as:

Objective: Find the feasible design(9)s. t. $LCL_i \le x_i \le UCL_i$

 $LCL_j \le y_j \le UCL_j$ and (8)

As discussed in the above, it is difficult to find the explicit objective function in Equation (2). Different design methodologies may have the different approaches to evaluate the "goodness". For instance, the decision-based design prefers the design decision whose expectation has the highest value [17]. Instead of the specific option, the whole design space is given out in the POC. The constraint parameter space is made up of the cells x_j vs. x_j . The m*(m-1)/2 cells, each of them represents a 2-dimensional design space of two parameters, is employed to visualize the m-dimensional design space (m is the number of the design parameters) as shown in Figure 9.

The design space of two parameters is bounded by the half spaces of the constraint in Equation (2). In the linear case, the boundary of the half space is the straight line. In other words, the design space is located on one side of any boundary. Therefore, the design space is convex in linear problem. Unfortunately, the same rationale also gives us concave design space for the non-linear problem will not be convex.

Feasible Performance Space: The same graphical representation in the constraint parameter space can be applied to the performance attributes to form the feasible performance space. The n*(n-1)/2 cells describe all possible performance attributes satisfying the constraints in Equation (2). As the analytical solution of feasible performance space is still under the development, two simulation-based methods are inspected. Monte Carlo method randomly selects the design parameters, and Grid Simulation enumerates the design options on the equally divided grid point of the design parameters. While the point sets of grid simulation is more close to the reality than Monte Carlo method, it generates lots of redundant experiments in the graphic matrices of the POC.



Figure 9. POC Applied to a Linear Problem

The performance-based representation uses the Performance Orientation Chart to aid the decision maker throughout the design process. The graphic matrices, which are integrated in the POC, make the intrinsic attributes of the design visible to the designer. Although still under the importation growth, the representation enables us to grasp the extensive understanding of current design option and assist the designer in making a reasonable design decision.

Conclusions

The research has led to three significant advances in systems synthesis. First, a development process has been implemented that facilitates cost estimation between designer and manufacturer. This process leverages current investment in information technology and can be directly embedded in current STEP-compliant systems. Second, a method for design evaluation has been developed to provide flexibility in environments with variation and uncertainty. Finally, a representation has been developed to explicitly evaluate the linkages and constraints in complex systems. Together, these techniques provide powerful new approaches for complex systems design. Our current focus for the next year is the completion of these concepts and formal documentation for wide-area dissemination.

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