Managing Extended Producer Responsibility using PLM
Part 1: Ensuring Compliance in Early Design Stages

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ABSTRACT

Concerns about the environmental impacts of used and discarded products have recently led to enactment of laws that regulate the amounts of hazardous substances and recyclable content in products. The laws also make the Original Equipment Manufacturers (OEMs) responsible for recovery and proper treatment of these end-of-life products. In this two part paper, we present methodologies for OEMs to use the PLM framework to effectively meet the challenges posed by these regulations. In this first part, we provide a methodology to proactively select material and processing specifications in early design stages, so as to ensure compliance. The methodology uses of chance constrained programming to account for uncertainty. We also discuss the scope and limitations of the approach. In Part 2 of this paper, we will present a methodology for case-by-case selection of the treatment strategy for incoming end-of-life products.

Keywords: environmental regulations, chance constrained programming, PLM.

1. INTRODUCTION

The growing amounts of waste generated by used and discarded products, along with increased awareness about harmful effects of specific substances in these waste streams, has given birth to laws that make the manufacturers responsible for the recovery and treatment of their end-of-life products. Such so-called Extended Producer Responsibility laws have already been enacted in Japan, Germany and certain European countries. The European Union has passed directives that would require all member states to enact similar laws [3-5]. In the US, solid waste arising from disposal of products is governed by the Resource Conservation and Recovery Act (RCRA) in the Code of Federal Regulations [16]. Although the regulations differ depending upon the country and the product category, they usually include the following three types of clauses:

1. bans and/or restrictions on the use of certain hazardous substances,
2. stringent requirements on amounts of material to be recovered and recycled from end-of-life products, and
3. transfer of financial, and in some cases operational, responsibility of collection and treatment of end-of-life products onto the OEM (Original Equipment Manufacturer).

In today's competitive environment, OEMs strive to be the first to bring new, innovative, and high quality products to the market. But modern consumer products are complex and a number of stakeholders are involved in the production, distribution, maintenance, and recovery & recycling of the products. The OEM must ensure that all in-house and procured components, as well as the product as a whole, conform to applicable limits and requirements. They also need to plan the recovery and treatment of discarded products to ensure that the regulations for safe disposal and targets for recycling/refurbishment are satisfied. Such treatment may be done directly by the OEMs or through Authorized Treatment Facilities (ATFs).

Developing innovative products, while avoiding costs and delays due to regulatory violations or sub-optimal treatment strategies, is a challenging task for the OEM. It requires a systematic approach that gives adequate consideration to all steps in the product's lifecycle, by taking feedback from all stakeholders. Such an approach is enabled by Product Lifecycle Management (PLM), a new and evolving paradigm for managing the creation and sharing of product information across the extended enterprise. PLM has been defined as a strategy that provides a structured framework to facilitate collaboration both internally and externally among strategic partners throughout a product's life cycle from initial concept and design through operation, maintenance and retirement [1]. It aims to facilitate innovation by allowing faster and effective information exchange, use of past knowledge, and seamless collaboration between various functions of the enterprise.

Through this two part paper, we develop methodologies for manufacturers to effectively address these regulatory challenges using the PLM framework. In the first part, we focus on selecting suitable material and processing specifications for components, so as to account for regulatory compliance in addition to production costs and quality. The paper builds upon our work reported earlier [11], which described an overall methodology and demonstrated the use of chance constrained programming to enable this selection in the early design stages when properties, such as production costs, amounts of hazardous substances contained, or performance, etc., are not deterministically known for the different component alternatives. In this paper, we explain the methodology and the solution approach using an example. We also include a discussion about the scope and limitations of the different steps in the methodology as well as the resources required at each stage.

Part 1 of this paper is organized as follows. Section 2 provides a brief survey of literature relating to issues in selection of component specifications in early design stages. Section 3 briefly describes the proposed framework for consideration of environmental regulations during selection of component specifications. Section 4 explains the mathematical model developed for the problem, and the algorithm to solve the model. Section 5 includes a discussion of the limitations of the proposed methodology, in its current form, and directions of future research to address these limitations. Section 6 concludes this part of the paper and summarizes the contributions.

2. BACKGROUND

The design of new products can be broadly classified into three stages: conceptual design, embodiment design, and detail design [14]. Decisions about material and processing specifications for components (e.g., heat treatments, surface coatings) as well as performance requirements are made in the embodiment design stage. Since hazardous substances contained in a component are implicitly dependent on these requirements, the corresponding limits should also be specified at the same time. In order to ensure compliance, OEMs often transfer the regulations applicable to the product uniformly to all components of the product, or enforce their own, stringent requirements on the suppliers. The ability and costs of producing components to meet these specifications, or the expected performance of the resulting components is seldom given adequate consideration. Consequently, undue pressure is placed on the suppliers of certain components, which become difficult to manufacture without excessive costs or reduction in quality. After detail design of components is completed, suppliers are required to provide information about the amounts of hazardous substances in their components, which is used to validate compliance. Costly design changes are often necessitated if regulatory violations, technical infeasibility or unacceptable loss of quality is detected in the later design stages.

To the best of our knowledge, the selection of hazardous substance and recyclable content specifications for components, in the embodiment design stage, has not been previously studied in literature. However, some methods to incorporate other considerations during embodiment design have been discussed. Vairaktarakis [19] presents a method for obtaining the optimal parts mix for a product subject to budgetary constraints, when alternative choices for each part are given. The importance of individual parts in the overall product, as well as performance ratings for each alternative choice, are calculated using house of quality matrices in a QFD (Quality Function Deployment [8]) style approach. Subsequently, a linear programming problem is formulated to select the optimal parts mix. Kuppuraju, et al. [13] present a technique that involves creation of alternative concepts, selection of most-likely-to-succeed concepts, and formulation of selection-decision-support problems to rank feasible alternatives in order of preference. The method concentrates only on quantifying and comparing desirable attributes to decide relative rank, and does not account for quantitative requirements or constraints. Moreover, both the methods mentioned above assume detailed and accurate knowledge is available for all alternative design concepts.

As in the case of selection of regulated substance specifications, uncertainty about input variables is encountered in a number of practical engineering problems. Such uncertainty is often sought to be wiped out using mean or expected values. However, this may lead to a high probability that the solution obtained will be infeasible. The other approach is to look for a conservative solution, i.e., one that is feasible in all possible cases. Such a solution, often called a “fat solution”, reflects total risk aversion on the part of the decision maker, and is often very expensive [12]. In order to overcome these issues, different approaches (e.g., reliability analysis, robust optimization, stochastic programming, etc.) have been suggested to tackle uncertainty in different domains of decision-making problems.

Chance constrained programming [9], a class of stochastic programming, is often the most suitable approach for single step decision problems, where it is difficult to quantify the costs of corrective actions or penalties faced if the solution obtained is infeasible. Constraint equations are modeled such that the coefficients of the decision variables have known probability distributions. For each constraint, the user can specify the probability with which the constraint must be satisfied (or the acceptable risk of the constraint being violated). This approach is suitable for the embodiment design stage, where properties of component alternatives, such as costs, weight, surface area to be coated, etc., can be estimated in terms of probability distributions.

The methodology presented in this paper, builds upon the method suggested by Vairaktarakis [19] incorporating constraints arising from regulatory requirements, as well as enabling consideration of uncertainty using probabilistic input and chance constraints. We also present a framework for implementing this method in an enterprise setting using PLM.

3. FRAMEWORK FOR SELECTION OF SPECIFICATIONS FOR COMPONENTS

Traditionally, the conceptual and embodiment design phases are carried out in-house by a core team of designers at the OEM. Considerable experience and knowledge about production of individual components is required from these designers in order to prescribe the material and processing specifications for each component in the chosen design configuration. Restrictions on regulated substances contained in each component also need to be specified at this time, since they will affect the choice of material and processing specifications. However, it is unreasonable to expect the designers to know intricacies, such as regulated substance contents, or recyclable material content, etc., for various alternative methods of making a component. Such information should ideally be obtained from experts, i.e., from the respective component manufacturers and vendors.

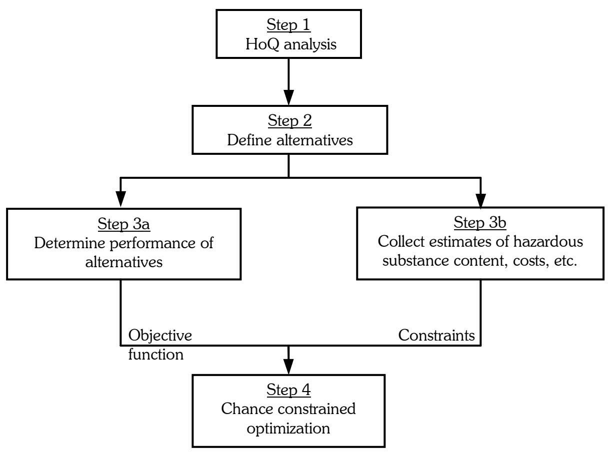


Fig. 1: Steps for selecting regulated substance content specifications for product components.

Today's PLM systems allow formation of cross-functional design teams along with involvement of suppliers and vendors, early in the design process. They provide the ability to query and retrieve data from third-party databases (e.g., databases of applicable regulations, material composition databases), as well as secure access functionality to enable feedback from the suppliers in these early design stages. In this section, we briefly present the framework for selection of material and processing specifications for components. The framework combines consideration of regulatory requirements, which are quantitative but indeterministic in the early design stages, with a rankings-based approach, similar to that used by Vairaktarakis [19] and Kuppuraju [13]. We assume that a design configuration has already been chosen in the conceptual design phase, and the specifications need to be decided for the components of this configuration. Fig. 1 shows the steps involved in the framework. The reader is referred to [11] for details and description of each step.

Step 1 involves quantification of qualitative information - e.g., relative importance of strength and corrosion resistance in a component's performance, relative importance of individual components in the overall product performance, etc.

Standalone software tools, using HoQ analysis or pairwise comparison methods, are available for such quantification, and can be readily integrated with an existing PLM system. Definition of alternative specification sets, in Step 2, requires knowledge of available technologies for making each component. This would require the design team to share expectations about functional properties with the suppliers or domain experts, and seek feedback with regards to the suitability of the alternative technologies. A standardized representation to describe the alternative specifications within the PLM system may be required to automate generation of queries and collection of estimates in the subsequent steps. However, development of such a standard is outside the scope of this research. Steps 3a and 3b require the design team to obtain quantitative estimates of cost, performance, hazardous substance content, etc., from the suppliers of each component. Systems for issuing requests-for-quotes are already used to gather information about component costs, and similar systems will be required to gather other information about the component alternatives. Moreover, recognizing the inherent uncertainty in determining these quantities at such an early design stage, the system must allow suppliers to provide estimates in terms of ranges or probability distributions. The final step, Step 4, involves the solution of an optimization problem to select the best set of specifications for each component in the product.

4. MANAGING UNCERTAINTY USING CHANCE CONSTRAINTS

The main challenge in the framework described above is to be able to make the choice of optimal specifications for each component although information about component alternatives is only available in terms of probability distributions. Overcoming this challenge requires use of stochastic optimization techniques. As described in section 2, chance constrained programming is the most suitable approach for such situations. In this section, we use a simple example to explain the formulation of the chance constrained programming problem and describe an algorithm to efficiently solve the resulting cases.

Consider that a design team has to design an industrial flow control valve for carrying a corrosive liquid. After comparing different options in the conceptual design phase, the team chooses a butterfly valve configuration, as shown in Fig. 2. For simplicity, let us assume that the only applicable regulation is a limit on the amount of hexavalent chromium (CrVI), which is contained in chromium plating, and that this limit is stated as an absolute value of 30 mg of CrVI per valve. Additionally, let us assume that the designers want to ensure that the production cost of the valve does not exceed $ 300.

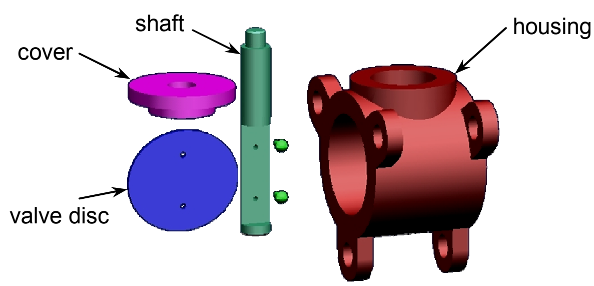


Fig. 2: Butterfly valve configuration.

As shown in Fig. 2, the valve configuration has four components (p_k), for which CrVI limit specifications have to be determined (the two screws are assumed to be standard inventory parts that do not contain CrVI). Let us consider that the relative importance (w_k) of each component, and the properties used for measuring the performance of the components are determined in Step 1 of the framework, and shown in Tab. 1. The subscript k ($k \in \{1,...,4\}$) denotes the component referred to by the variable, as shown in Tab. 1. Let us also assume that each component can be manufactured in only two ways; namely, without any chromium plating, or with chromium plating on the entire exposed surface area. Thus, the CrVI content specifications can be made by specifying whether the component should have chromium plating or not, i.e., there are two alternative specifications for each component. Each alternative is denoted by the subscript l, such that p_{kl} is the l^{th} alternative choice for k^{th} component ($l \in \{1,2\}$ for all k). A performance rating is obtained for each alternative by rating the expected performance of the alternative against the performance criteria defined in Step 1, and normalizing the ratings across the components. Since the detailed design of the components has not been completed, the exposed surface area of the components is not known, and the amounts of CrVI in chromium plated alternatives are estimated as normal probability distributions (represented by mean and standard deviation). Similarly, estimates of production costs for the alternatives are also available as normal distributions. This information about the component alternatives is tabulated in Tab. 2.

k	Component (p_k)	Performance Criteria	Relative Importance (w_k)
1	housing	castability case hardenability machinability corrosion resistance	5
2	cover	machinability hardenability	2
3	valve disc	machinability corrosion resistance	3
4	shaft	machinability hardenability corrosion resistance	3

Tab. 1: Performance criteria and relative importances of each component.

Component p_k	p_{kl}	Description of alternative	CrVI content H_{kl} (mg)		Cost c_{kl} ($)		Performance Rating $\Re_k$
			$\overline{H_{kl}}$	$\sigma_{H_{kl}}$	$\overline{c_{kl}}$	$\sigma_{c_{kl}}$	
housing	p_{11}	ductile iron	0	0	95	2	5
	p_{12}	ductile iron with Cr plating	19	2.1	145	2	7
cover	p_{21}	medium carbon steel	0	0	45	2	5
	p_{22}	medium carbon steel with Cr plating	2.2	0.3	65	2	7
valve disc	p_{31}	ductile iron	0	0	35	2	5
	p_{32}	ductile iron with Cr plating	8	0.8	55	2	7
shaft	p_{41}	medium carbon steel	0	0	45	2	5
	p_{42}	medium carbon steel with Cr plating	6	1	65	2	6

Tab. 2: Information about component alternatives.

For the purpose of this research, we assume that only a finite number of discrete alternatives have been defined for each component. Correspondingly, we create binary decision variables denoting whether or not a particular component alternative is to be selected,

$$x_{kl} = \begin{cases} 1 & \text{iff } p_{kl} \text{ is selected for } p_k \\ 0 & \text{otherwise} \end{cases} \tag{4.1}$$

The following constraints on the decision variables are necessary to ensure that they can take only values 1 or 0, and that only one alternative can be selected for any component:

$$x_{kl} \in \{0,1\} \tag{4.2}$$

$$\sum_{l=1}^{2} x_{kl} = 1 \qquad \text{...for all } k \tag{4.3}$$

The objective function, which is to maximize the product's overall performance, is given by Eqn. (4.4).

$$\max \sum_{k=1}^{4} \sum_{l=1}^{2} w_k \Re_{kl} x_{kl} \tag{4.4}$$

Finally, the constraints arising from the chromium content regulation and the production cost requirement can be added to the formulation, as shown by Eqn. (4.5) and (4.6) respectively.

$$\sum_{k=1}^{4}\sum_{l=1}^{2} H_{kl}x_{kl} \leq 30 \tag{4.5}$$

$$\sum_{k=1}^{4}\sum_{l=1}^{2} c_{kl}x_{kl} \leq 300 \tag{4.6}$$

However, as discussed in the previous section, the properties of CrVI content (H_{kl}) or cost of production (c_{kl}) for each component alternative (p_{kl}) are not deterministically known. Instead, they are available as estimates and hence are probabilistic quantities. Solving a deterministic optimization problem using mean values can lead to a solution with a high probability of being infeasible, while using worst case values may yield a solution that is far from optimal. Instead, the chance constrained programming model works directly with the estimated probability distributions of these quantities, and allows the user to specify the minimum probability (α) with which any solution must satisfy a particular constraint. As explained in [11], the choice of α will depend upon a number of factors, such as confidence in property estimates, flexibility of design to make changes, lead time available for changes, penalties for non-compliance with the specific constraint, financial risk bearing capacity of OEM, etc. Consequently, in the chance constrained programming formulation, the constraints Eqn. (4.5) and Eqn. (4.6) will be converted into the following chance constraints:

$$P\left(\sum_{k=1}^{4}\sum_{l=1}^{2} H_{kl}x_{kl} \leq 30\right) \geq \alpha_1 \tag{4.7}$$

$$P\left(\sum_{k=1}^{4}\sum_{l=1}^{2} c_{kl}x_{kl} \leq 300\right) \geq \alpha_2 \tag{4.8}$$

Chance constraints in the form expressed above, where a probability is assigned for a single equation being satisfied, are referred to as “separate” or “individual chance constraints”. Often times it is more intuitive for the user to specify a probability for a set of constraints to be satisfied together. Such cases are referred to as “joint chance constraints" and will be of the form shown in Eqn. (4.9) below.

$$P\left(\sum_{k=1}^{4}\sum_{l=1}^{2} H_{kl}x_{kl} \leq 30; \sum_{k=1}^{4}\sum_{l=1}^{2} c_{kl}x_{kl} \leq 300\right) \geq \alpha \tag{4.9}$$

It should be noted that any regulatory requirement can be formulated in the form of a similar linear constraint equation. The reader is referred to [11] for formulation of constraint equations in the general case. In addition, one also needs to incorporate constraints of the form of Eqn. (4.10), which arise if an alternative for one component is incompatible with an alternative for another component. For example, a steel bolt cannot be specified in combination with a nylon nut. Such incompatibilities are usually found between mating parts. Reasons for incompatible part alternatives include possibility of local corrosion due to material combination at contact, unequal thermal expansion coefficients, unequal hardness causing excessive wear on one part, etc. For simplicity, we shall not include such constraints in the current example. However, it should be noted that such constraints are linear and deterministic, and their inclusion does not affect the solution methodology.

$$x_{ag} + x_{bh} = 1 \qquad \text{... for alternatives } p_{ag} \text{ and } p_{bh} \text{ which are not compatible with each other} \tag{4.10}$$

The nature of the constraint equations varies considerably between “individual” and “joint” chance constraints. Therefore, we consider two separate cases for handling the two types of chance constraints in order to solve the chance constrained programming formulation.

4.1 Case 1: Individual Chance Constraints

For the first case, let us assume that the design team is willing to accept a 10% risk on each of the constraints (i.e., for each constraint, there is a 10% chance that the solution, upon detail design, may end up violating the constraint). This means that the solution must have 90% probability of satisfying each constraint individually. Thus, probabilistic constraints will be expressed as:

$$P\left(\sum_{k=1}^{4}\sum_{l=1}^{2} H_{kl}x_{kl} \le 30\right) \ge 0.9 \quad (4.11)$$

$$P\left(\sum_{k=1}^{4}\sum_{l=1}^{2} c_{kl}x_{kl} \le 300\right) \ge 0.9 \quad (4.12)$$

Such individual chance constraints (ICC) can be converted into equivalent deterministic constraints by integrating over the resultant probability distribution function. However, deriving the deterministic equivalent is usually very difficult due to complicated multivariate integration and is only practical if the random variables involved follow certain distributions, namely normal, uniform, exponential and lognormal distributions [10]. For our example, the random variable coefficients are available as normal distributions. As explained in [11], we use the properties of normal sum distributions and cumulative normal distributions to convert the individual chance constraints into non-linear, deterministic constraints. These in turn, are reduced to linear, deterministic constraints using a conservative approximation shown by Segara, et al. [17]. Thus, the chance constraint equations – Eqn. (4.11) and Eqn. (4.12) – are replaced by deterministic constraints shown in Eqn. (4.13) and Eqn. (4.14) respectively, where Z is obtained from the standard normal distribution $N(0,1)$. ($Z = 1.2817$ for 90% probability).

$$\sum_{k=1}^{4}\sum_{l=1}^{2} \overline{H_{kl}}x_{kl} + Z\sum_{k=1}^{4}\sum_{l=1}^{2} \sigma_{H_{kl}}x_{kl} \le 30 \quad (4.13)$$

$$\sum_{k=1}^{4}\sum_{l=1}^{2} \overline{c_{kl}}x_{kl} + Z\sum_{k=1}^{4}\sum_{l=1}^{2} \sigma_{c_{kl}}x_{kl} \le 300 \quad (4.14)$$

When all the individual chance constraints are converted into linear deterministic constraints the chance constrained optimization problem is transformed into a binary (0-1) integer linear programming problem. Usual integer linear programming techniques, such as branch-and-bound or cutting plane methods, can be used to efficiently solve the problem. For the present example MATLAB's binary integer linear programming routine, which uses a branch and bound technique, was used to arrive at the solution. The resulting solution is shown in Tab. 3. The solution that would have been obtained using worst case estimates (i.e., using 99.8% confidence values for estimates) is also presented for comparison.

	Chance constrained model	*Optimization using worst case estimates*
housing	plated	plated
cover	not plated	not plated
valve disc	plated	not plated
shaft	plated	not plated
CrVI content (mg)	**mean = 27** $P(CrVI \le 30) = 0.909$ $P(CrVI \le 29.88) = 0.9$	**25.54**
Cost ($)	**mean = 290** $P(Cost \le 300) = 0.99$ $P(Cost \le 295.16) = 0.9$	**290**
Performance rating	**81**	**75**

Tab. 3: Results for case study (ICC problem).

4.2 Case 2: Joint Chance Constraints

Now, let us consider the case where the design team desires 90% confidence that the solution obtained, upon detailed design, will satisfy all the constraints involved. That means the solution must satisfy both the cost and the CrVI content constraints jointly with a probability of 90%. This is expressed mathematically in the following equation:

$$P\left(\sum_{k=1}^{4}\sum_{l=1}^{2} H_{kl}x_{kl} \le 30; \sum_{k=1}^{4}\sum_{l=1}^{2} c_{kl}x_{kl} \le 300\right) \ge 0.9 \quad (4.15)$$

Transformation of joint chance constraints (JCC) problems into deterministic problems leads to complicated non-linear constraints, which often lead to a non-convex solution space, although the individual constraint equations are linear and convex. Methods using Monte Carlo simulations or creation of polyhedral outer approximations of the solution space have been previously used for medium scale joint chance constrained problems with continuous variables. Other implementations involving discrete approximations of the constraint equations have also been used for problems with large number of constraints [9].

We use an algorithm to approximately solve the JCC problem by systematically solving a set of more conservative ICC problems that collectively approximate the feasible space for the original JCC problem. In order to do that, we assume that the estimated random variable coefficients, and consequently the constraint equations, are independent of each other. The consideration of correlated random variable coefficients is beyond the scope of this paper, but forms a part of our ongoing work as elaborated in section 5. Using this assumption, we can introduce two new parameters (ϕ_1 and ϕ_2) to replace the joint chance constraint Eqn. (4.15) by the following set of constraints:

$$P\left(\sum_{k=1}^{4}\sum_{l=1}^{2} c_{kl}x_{kl} \le 300\right) \ge \phi_1 \tag{4.16}$$

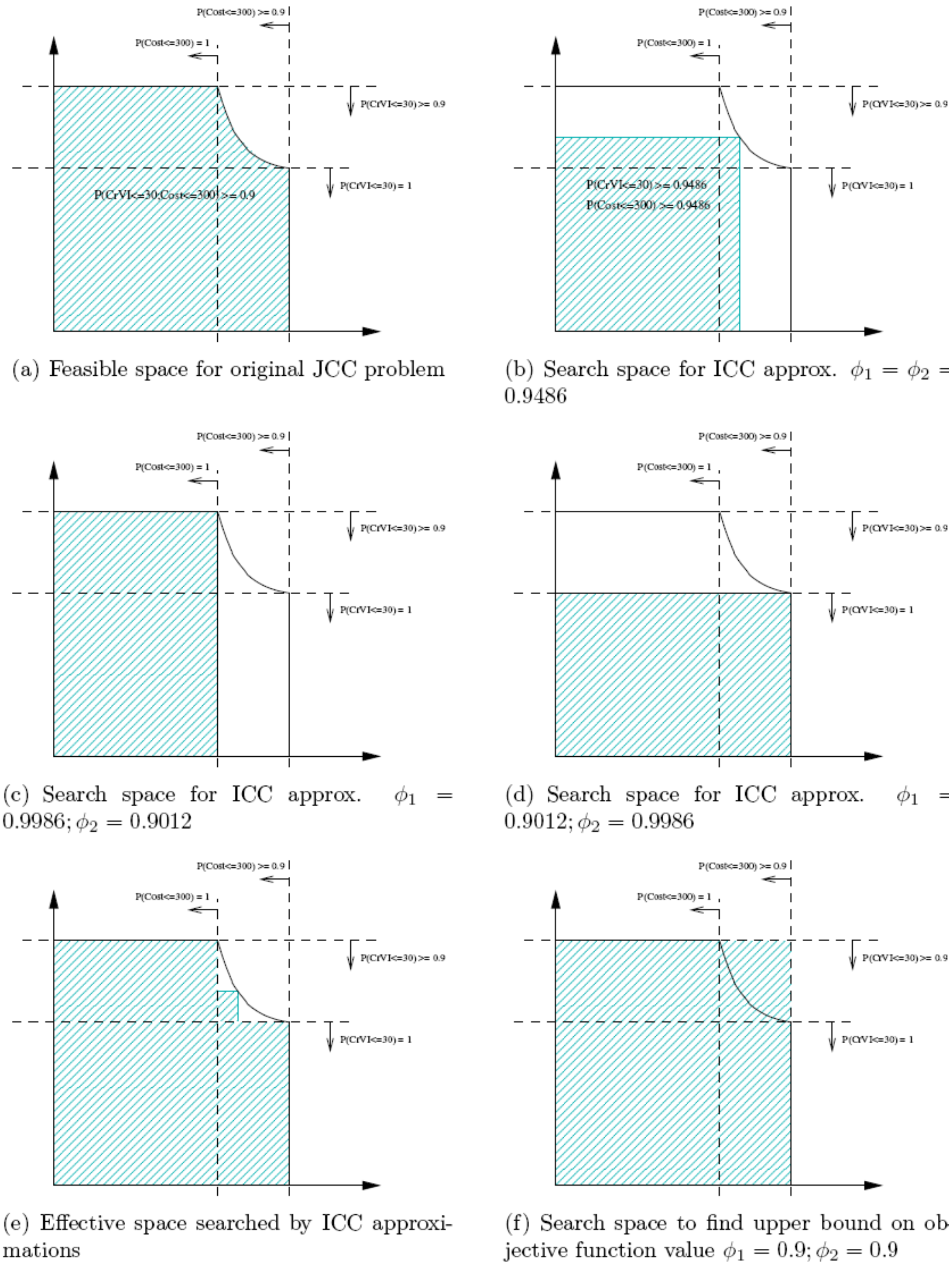
$$P\left(\sum_{k=1}^{4}\sum_{l=1}^{2} H_{kl}x_{kl} \le 30\right) \ge \phi_2 \tag{4.17}$$

$$\phi_1\phi_2 = 0.9 \qquad\qquad ...0 \le \phi_1, \phi_2 \le 1 \tag{4.18}$$

As shown in section 4.1, Eqn. (4.16) and Eqn. (4.17) can be transformed into linear, deterministic constraints. However, Eqn. (4.18) remains a non-linear, non-convex constraint. This constraint is eliminated by choosing values for ϕ_1 and ϕ_2, such that Eqn. (4.18) is satisfied, thus generating an ICC approximation for the JCC problem. The parameters ϕ decide the manner in which the acceptable risk of failure of the joint constraint is divided amongst individual constraints. Details of the process of choosing appropriate values for ϕ to systematically obtain successive ICC approximations are explained in [11].

In this paper, we explain this process for the valve design example. Consider that all combinations of alternatives are represented as discrete points on a plane, where the X-axis measures the probability of the combination meeting the cost constraint, while the Y-axis measures the probability of the component meeting the CrVI content constraint. Accordingly, Fig. 3(a) shows the feasible solution space for the JCC case, as defined by Eqn. (4.16), Eqn. (4.17), and Eqn. (4.18). Instead of searching for the optimal solution in this non-convex, non-polyhederal space, we solve a set of conservative ICC approximations. For the first ICC approximation, we divide the acceptable risk of failure of the joint constraint equally among the two individual constraints Eqn. (4.16) and Eqn. (4.17), and accordingly set $\phi_1 = \phi_2 = \sqrt{0.9} = 0.9486$. Consequently, the non-linear constraint Eqn. (4.18) can be discarded. The solution space searched by this ICC problem is shown in Fig. 3(b).

Subsequently, we solve two more ICC approximations by allowing the entire acceptable risk to be taken up completely by one of the individual constraint at a time. The solution spaces searched are shown in Fig. 3(c) and Fig. 3(d). It should be noted that since the random variables in our case are normally distributed, it is not possible for any solution to meet a constraint with 100% probability. Therefore, we consider that the solution meets the constraint at all times if it meets it with 99.86% probability (which corresponds to the commonly accepted 3σ limit). Consequently in order to stay within the specified acceptable risk, the remaining constraint has to be satisfied with 90.12% probability. The total solution space searched by all three ICC approximations together is shown in Fig. 3(e). The optimal solutions obtained for the three ICC approximations are shown in Tab. 4 below. Accordingly, the solution where chromium plating is specified on the housing and the cover and has a performance rating of 79 is selected as the solution for the JCC problem.



(a) Feasible space for original JCC problem

(b) Search space for ICC approx. $\phi_1 = \phi_2 = 0.9486$

(c) Search space for ICC approx. $\phi_1 = 0.9986; \phi_2 = 0.9012$

(d) Search space for ICC approx. $\phi_1 = 0.9012; \phi_2 = 0.9986$

(e) Effective space searched by ICC approximations

(f) Search space to find upper bound on objective function value $\phi_1 = 0.9; \phi_2 = 0.9$

Fig. 3: ICC approximations to JCC problem.

	ICC approx. #1 $\phi 1=\phi 2=0.9486$	*ICC approx. #2* $\phi 1=0.9986$ $\phi 2=0.9012$	*ICC approx. #3* $\phi 1=0.9012$ $\phi 2=0.9986$	*ICC approx. for upper bound* $\phi 1=\phi 2=0.9$
housing	not plated	not plated	plated	plated
cover	plated	plated	plated	not plated
valve disc	plated	plated	not plated	plated
shaft	plated	not plated	not plated	not plated
CrVI content (mg)	mean = 16.2	mean = 10.2	**mean = 21.2**	mean = 27
Cost ($)	mean = 280	mean = 260	**mean = 290**	mean = 290
Performance rating	78	75	**79**	81

Tab. 4: Results for case study (JCC problem).

The last column in Tab. 4, shows the solution obtained for an ICC problem in which each of the individual constraints have to be satisfied with the same probability specified for the joint chance constraint. Clearly, this problem includes solutions that violate the JCC problem. However, as shown in Fig. 3(f), the feasible space for the JCC problem is a subset of the feasible space of this problem. Consequently, the solution to this problem provides an upper bound on the performance rating of the solution to the JCC problem. In JCC problems involving a large number of constraints, this upper bound can be effectively used to terminate the successive solution of ICC approximations if a solution with performance rating sufficiently close or equal to the upper bound is obtained.

5. LIMITATIONS

In its current form, the framework presented in the previous sections has certain limitations. The number of assessments required in the House of Quality analysis increases rapidly as the number of components in the product and the number of performance criteria increase. When these assessments, as well as assessments of component performance, are carried out by multiple evaluators, procedures to adjust for differences in application of rating scales will be required. Thurston [18] provides a discussion of limitations of the utility assessment procedures, and bias due to preferences of team members, when using utility analysis for design tradeoff problems. Advances reported in literature towards overcoming these limitations, will be studied in future to improve the scalability and consistency of the evaluation steps.

For our initial work, we approximate the overall product performance using a weighted sum of individual component performances. As a part of our ongoing work, we shall use separate functions to aggregate component performances in each criterion, to account for non-linear and non-compensating behavior of performance attributes. Subsequently, a multi-objective optimization problem shall be formulated considering all attributes that contribute to the product's performance.

As mentioned in section 4.2, the method for solving the joint chance constrained problems requires that the random variable coefficients are mutually independent. However, covariance between different uncertain parameters is often observed in practical cases. The relation between the parameters can be defined using covariance matrices or conditional probability distributions. We plan to study the effects of this covariance on the solution methodology. We shall also study the feasibility of using continuous variables to represent choice of certain specifications, thus formulating the problem as a mixed continuous-integer variable problem.

These limitations will have to be addressed in order for the framework to be used in for practical cases by any original equipment manufacturer.

6. SUMMARY

In this part of the paper, we addressed one aspect of challenge posed by Extended Producer Responsibility laws, namely, the selection of material and processing specifications to ensure compliance. We have presented a new approach to account for regulatory requirements early in the design phase, with the aim of reducing downstream costs of compliance. The framework presented aims to use the recent advancements in PLM software capabilities to make more informed decisions. The method accounts for the uncertainty about component properties in early design stages, and allows the design team to explore innovative design combinations, while setting limits on the chances of violating regulatory requirements. The method can be extended to incorporate additional design considerations that are characterized by uncertainty in early design stages.

Original Equipment Manufacturers (OEMs) today, are preparing to face a considerable financial burden due to Extended Producer Responsibility. The American electronics industry estimates that increased material costs, for compliance with the directive on Waste Electrical and Electronic Equipment (WEEE) [6], will run from $140 to $900 million [20]. In a separate report, analysts estimate that requirements of the End of Life Vehicles (ELV) directive [3] might result in an additional €20 to €150 per vehicle in costs for compliance [7]. While a portion of this cost can be attributed to newer materials and processes to meet substance content regulations, a major portion also stems from the recovery and treatment of end-of-life products, which is enforced upon the OEMs. In the second part of the paper, we present a methodology to choose the most suitable and economical treatment strategy for incoming end-of-life products on a case-by-case basis. Previous studies towards this goal have relied upon specialized representations of the product that have to be generated by human experts since CAD representations do not store information about joints between components, and often even the geometry of joints is not completely modeled in CAD. We present rule-based algorithms that draw inferences from the component geometry to extract information about the types of joints between parts, and their location, size, orientation, etc. directly from CAD assembly models. This shall enable efficient selection of the treatment strategy within a PLM framework, without the need for any specialized representations of the product.

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