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RISK EFFECT MINIMIZATION USING FLEXIBLE PRODUCT AND PROCESS DESIGN

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ABSTRACT

This paper addresses robust product development practices by evaluating the flexibility of the development process and the resulting product and process designs. A flexible design has the ability to change performance while requiring only minor time and costs to change the design parameters. A design change might be necessary if the actual design performance is not matched by the predicted design performance. The described methodology utilizes response surfaces for multiple performance attributes to assess the utility across the design space. This utility is optimized with respect to the robustness against noise and prediction inaccuracies. Based on this design, non-dominant pareto optimal sets of all feasible design changes are then developed to asses potential performance gains against the time and cost needed to incur the change assuming correct performance predictions. While robust design practices seek to reduce the risk of design change, the proposed method rather accepts the risk of design change and minimizes the potential negative effects.

KEYWORDS

Flexible Design, Design Change, Pareto Optimal Design, Change Cost, Robust Design, Product Design, Process Design

NOTATION

μ_y	Mean of predicted response *y*
μ_e	Mean of response error *e*
μ_z	Mean of actual response *z*
σ_y	Deviation of predicted response *y*
σ_e	Deviation of response error *e*
σ_z	Deviation of actual response *z*
λ	Error factor
λ_j	Minimum error factor to justify change *j*
ΔB	Vector of benefit loss for variable combinations *S*
ΔC	Vector of savings for flexible change vs. inflexible change
Δt	Vector of change time for variable combinations *S*

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B	Vector of benefits for variable combinations S
C^C	Vector of cost of change for variable combinations S
C^M	Vector of material cost for one part
C^P	Vector of process cost for one part
C^T	Vector of cost of task T
ES	Vector of Expected Savings for variable combinations S
$f_e(e_i)$	Probability density distribution for the prediction error e_i
$f_y(y_i)$	Probability density distribution for the response y_i
$f_z(z_i)$	Probability density distribution for the combined response variation and prediction error
LSL	Vector of lower specification limit
m	Number of responses in Y
n	Number of variables in X
NS	Vector of net savings for variable combinations S
P_j^{DC}	Probability of change j
S	Vector of combinatory sets S_j
S_j	Vector of combinatory set of variables of X
Q_j	Set of tasks needed for change of x_i
T_k	Task k
t^T_k	Time required for task T_k
U	Utility function
USL	Upper Specification Limits
V	Production volume
x	Design parameter of X
X	Vector of all input variables
X_j	Vector of input variables for optimal design for changes in S_j
X_{Start}	Starting point of the algorithm
y	Specified response
Y	Vector of all specified responses

GLOSSARY

Robust Design: Design robust against variations due to noise, however, this does not include prediction errors, and the performance prediction for this robust design may be wrong due to prediction inaccuracies.

Error Proof Design: Design robust against variations due to noise and due to prediction inaccuracies, may not necessarily be the most economic design possible. An error proof design is also a robust design, but not all robust designs are error proof.

Flexible Design: Design robust against noise, but also flexible to allow design changes with a minimum effort of cost and time.

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INTRODUCTION

This paper presents a methodology to preventively minimize the negative effect of design changes using a flexible design approach. The standard engineering approach utilizes the robust design providing the optimum performance within the allowed design space with respect to variation and uncontrollable variables, i.e. the design will be robust against noise. Now the question arises, if this point has the optimum utility and is robust against noise, then why is there any need to change it?

However, this optimal point was determined using models, simulations or experiments, and there is a possibility that the physical embodiment of the design might not satisfy the specifications due to possible model inaccuracies. Although the design prediction considers noise, it does not account for errors and inaccuracies in the predictions of the design performance.

Due to this lack of consideration for inaccuracies, the finely tuned robust design might violate specifications because the underlying predictions lack the necessary accuracy. This violation of the specifications would then create the need for a design change, even if the model predicted this design to be optimal. Depending on the violated specifications and the probability of violation, additional cost is created due to the necessary quality control, the discarding of defect parts, unsatisfied customers and so on. A design change could be created to remedy these deficits, reducing the cost due to defect parts. On the downside, however, this change in the design also creates cost and delays the production of the part. To prevent this problem, it is possible to design the product to reduce the risk of design change by not only including the noise into the robust design, but also make the design robust against prediction inaccuracies. This type of design is nominated as error proof design throughout this paper.

However, this error proof design may reduce the overall utility of the design and increase the cost, creating a sub-optimal robust design. Also, note that the prediction error can be reduced by increasing the knowledge about the design relations. This knowledge can be gained for example during the production of the design, providing higher prediction accuracy and enabling the design team to improve the design based on improved predictions. With this knowledge, it would be beneficial to improve the performance by changing the robust design. However, a design change can be very costly, and the possible performance benefits may be outweighed by the change effort.

This paper proposes a method to select an optimal design robust to noise, therefore avoiding a performance loss due to prediction error robustness. At the same time, the design is also selected for flexibility to allow easy changes to the design in case of prediction inaccuracies by minimizing the cost and time required for a change in input parameters. This methodology will assist the designer with creating a flexible design for risk effect minimization by comparing the performance of a design with the risk and benefits of design change. The following sections detail the methodology, followed by an example and conclusions.

METHODOLOGY

Figure 1 shows an overview of the design methodology. The methodology starts by determining the description of the system, where the input variables, the design responses, and the related transfer functions are determined. This is the knowledge base for the methodology. Next, the design team has to select which input variables will be investigated in further detail as possible design changes.

Parallel to this task, an error proof design has to be found. This error proof design is a very conservative design, robust against variations due to noise and due to inaccurate model predictions, so the probability of a design change for this robust design is very

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low. However, due to the extremely conservative design assumptions, this error proof design may also be less efficient than other robust designs.

Here it is important to note the difference between noise and prediction errors. Noise is uncontrolled random variation, which is different for every sample, i.e. every produced item. Therefore, it is not possible to adjust the process to avoid the difference between the mean response and the sample response. On the other hand, the prediction provides an estimated response, which may differ from the actual responses of the designs. For a large number of samples an average difference can be determined, and the process can be adjusted to avoid those offsets. Therefore it is not possible to adjust for noise, but it is possible to adjust for prediction errors.

During the design process, however, this offset is not known, and therefore can not yet be adjusted for. Therefore, it is not known, if and how the actual design has to be changed. In this methodology, the change of the actual design is assumed to create the conservative error proof design to evaluate the flexibility of the actual design, where the flexibility of the design represents the ease of changing the design variables and their effect on the performance parameters. This error proof design can be created by combining the noise and the error distributions to optimize this error proof design.

Next, all combinations of input variables will be determined. Considering noise variation only, the optimum robust design is determined while changing only the allowed input variables. Also, the time and cost required to perform the various changes are estimated, along with the benefits resulting from these changes. These three information vectors are then compared to generate a trade off between the change cost, time, and benefit. The design change option having the best trade off is selected as the recommended design.

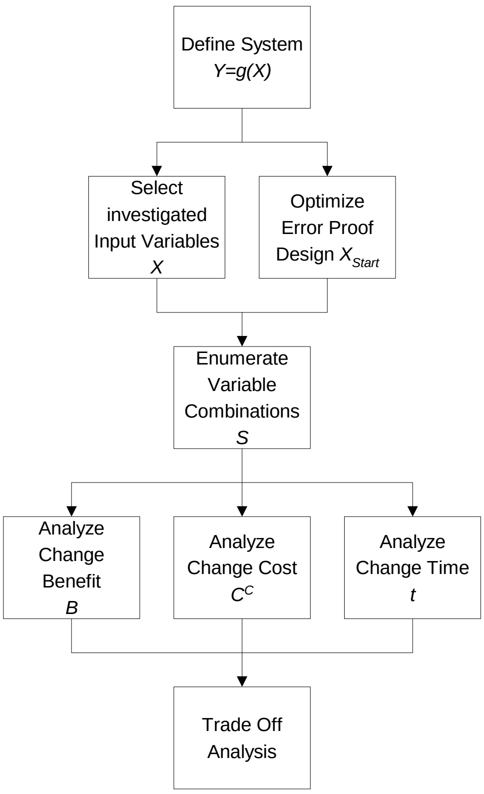

Figure 1: Methodology Overview

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System Description

The following knowledge regarding the design system is required to perform the proposed methodology. The extreme specification limits have to be known; also the relation between the input variables *X* and the specified output responses *Y* as described below. This relation can be based on experimental data, numerical, or analytical models. To reduce computation time it is advisable to consider only the input variables in *X* which show an effect towards the performance parameter (Roser et al., 1998).

$$Y = g(X)$$
$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix}; \quad X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \qquad [1]$$

In order to compare different designs in a quantitative way, the specified responses have to be combined into one single utility representing the desired performance parameters and their trade off relations in order to compare different designs. If the responses are not combined, it is difficult to trade off the improvement of one performance attribute with the negative change of another performance attribute.

The combination of the responses can be done by using a utility function *U*, according to the related specification limits. For example, a cost utility or a quality utility can be used as a utility function. However, a cost utility is preferred because of the facilitation of the direct comparison with the cost of the design change. This utility function must be defined before the methodology can proceed. (Chen et al., 1998) defined a quality utility function using a compromise programming method in order to achieve a robust design. In another paper, (Chen et al., 1996) improves the robust design method of variation minimization. (Keeney, 1974) describes multiplicative utility functions in comparison to additive utility functions. (Otto et al., 1993) implements uncertainty using the method of imprecision in comparison to utility theory approaches. (Hamada, 1992) improves Taguchi's robust design method, however (Wilde, 1991) states that Taguchi's signal to noise ratio is not necessarily a good measure for robustness. The proposed methodology defines utility based on the process cost C^P, the material cost C^M, and the probability of satisfying the specifications for a given design *X*:

$$U(g(X)) = \frac{C^P + C^M}{P\left(\left(LSL_1 \le y_1 \le USL_1\right) \wedge \ldots \wedge \left(LSL_i \le y_i \le USL_i\right)\right) \forall i} \qquad [2]$$

The process cost is a function of the machine operation costs and the operation time, the material cost is based on the material consumption and the material price. The probability of specification satisfaction for one specification is the integral of the response distribution between the lower specification limit and the upper specification limit as shown below.

$$P\left(LSL_i \le y_i \le USL_i\right) = \int_{LSL_i}^{USL_i} f_y(y_i)\,dy_i \qquad [3]$$

For independent variables, the joint probability of specification satisfaction is the product of the single probabilities of specification satisfaction.

$$P\left(LSL \le Y \le USL\right) = \prod_{i=1}^{m} P\left(LSL_i \le y_i \le USL_i\right) \qquad [4]$$

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Error Proof Design

The algorithm starts with the optimized robust error proof design in the design space. This error proof design is nominated as X_{Start}. Much research has been done in the area of robust design. The doctoral thesis of (Chen, 1995) describes a robust concept exploration method for the early design stages of complex systems. Further reading can also be found in the literature review of this thesis. (Ford et al., 1995) also addresses fundamental robust concept design issues. Yet there is little research regarding the handling of uncertainty in robust design. (Chipman, 1998) describes a method to handle uncertainty in robust design using Bayesian methods.

The error proof design does not only consider the response distributions due to noise in the responses $f_y(y_i)$ but also the probability distribution $f_e(e_i)$of the prediction error when determining the probability of specification violation. In order to estimate the probability of violating a specification, the probability density function of the response $f_y(y_i)$ and the probability density function of the prediction error $f_e(e_i)$ has to be known. Probabilistic methods can be used to determine the probability of violating the specifications. Note, that $f_e(e_i)$ includes not only the additional variation due to the error but also possible offsets from the predicted response mean.

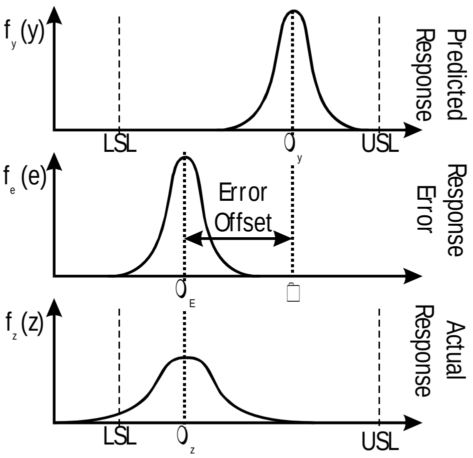

Figure 2: Response Distributions

The actual response z_i is now the sum of the two random variables of the predicted response y_i and the error e_i as shown in Figure 2 and evaluated below.

$$z_i = y_i + e_i \qquad [5]$$

According to (Papoulis, 1991) this can be considered a function of two random variables and evaluated:

$$f_z(z_i) = \int_{-\infty}^{\infty} f_e(z_i - y_i) \cdot f_y(y_i) dy_i \qquad [6]$$

For standard normal distributed random variables this equation can be simplified and the mean and the deviation of the joint distribution can be evaluated as shown below.

$$\mu_{z_i} = \mu_{y_i} + \mu_{e_i}$$
$$\sigma_{z_i} = \sqrt{\sigma_{y_i}^2 + \sigma_{e_i}^2} \qquad [7]$$

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In order to get the probability of specification satisfaction for the combination of both random variables, the density function has to be integrated accordingly.

$$P(LSL_i < z_i < USL_i) = \int_{LSL_i}^{USL_i} f_z(z_i)\,dz_i \qquad [8]$$

The error proof design point X_{Start} is then optimized to improve the design utility.

$$U(Z) = \frac{C^P + C^M}{P\left(\left(LSL_1 \le z_1 \le USL_1\right) \wedge \ldots \wedge \left(LSL_i \le z_i \le USL_i\right)\right) \forall i} \qquad [9]$$

Design Variable Combinations

In order to determine a flexible design, possible combinations of changes in the design variables have to be analyzed and their costs and benefits compared. If there exist *n* investigated input variables, there will be 2^n possible sets of design change combinations. These sets are nominated as S_j, with *j* ranging from one (no variables are allowed to be changed) to 2^n (all variables can be changed) as shown below.

$$S = \begin{bmatrix} 0 & 0 & 0 & \ldots & 0 \\ 1 & 0 & 0 & & 0 \\ 0 & 1 & 0 & & 0 \\ \vdots & & & \ddots & \vdots \\ 1 & 1 & 1 & \ldots & 1 \end{bmatrix} \cdot \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{bmatrix} \qquad [10]$$

$$S_1 = [0,0,0,\ldots 0]$$
$$\vdots$$
$$S_{2^n} = [x_1, x_2, x_3, \ldots x_n]$$

Change Benefit Analysis

Next, the methodology will be used to evaluate the benefit loss ΔB_j, change costs savings ΔC_j and change times Δt_j caused by changing a combination of input variables S_j. In order to evaluate the benefit loss ΔB_j, the benefits B_j of a possible change have to be determined. Those benefits are represented by the improvement of the utility compared to the utility at the starting point X_{Start}. In order to determine the maximum possible improvement, the utility has to be optimized by modifying the input variables in S_j and holding the remaining input variables constant at X_{Start} as shown in more detail below. (Reklaitis et al., 1983) provides an introduction and description of a variety of optimization methodologies and their application, including random search methods.

This methodology can utilize a wide range of optimization methods. (Osyczka, 1985) describes multicriteria optimization for engineering design, also providing a detailed algorithm. (Olsen et al., 1989) provides a nonlinear optimization algorithm including discrete variables. (Kunjur et al., 1997) implemented robust design techniques into a multi criteria optimization approach. (Jain et al., 1993) provides a multi-start optimization for highly nonlinear problems, providing the global optima. (Allwright, 1976) compares the conjugate gradient optimization method with the steepest descent method, proving the superiority of the conjugate gradient method for quadratic functions. Many other relevant approaches have been developed to solve optimization problems. Thus, the utility *U* of each candidate *j* is optimized towards a more robust (but not error proof) design. The benefit of changing from the error proof design X_{Start} to the robust design X_j is evaluated as shown below.:

$$B_j = Max\{U(g(S_j, X_{Start} \wedge (\neg S_j)))\} - U(g(X_{Start})) \qquad [11]$$

using Boolean *AND* "$\wedge$" and *NOT* "$\neg$" operators, where S_j is the set of variables from X which are changed in order to optimize the design. Of course, if the utility is a cost utility, then the optimal cost is the minimized utility, as shown below.

$$B_j = U(g(X_{Start})) - Min[U(g(S_j, X_{Start} \wedge (\neg S_j)))] \qquad [12]$$

The benefit loss ΔB for the more flexible designs is expressed as the difference between the benefit B_{2^n} of the optimal robust design and the benefit B_j for the current design X_j. Depending on the direction of the optimization of the utility this benefit loss is evaluated as shown below. Note that the optimal design for X_{2^n} is also the proposed optimal design for the system, as all variables are selected for optimization.

$$\Delta B_j = \begin{cases} B_{2^n} - B_j & if\ Max(U) \\ B_j - B_{2^n} & if\ Min(U) \end{cases} \qquad [13]$$

Change Cost Analysis

Next, the cost of changing the input variables has to be determined for all possible design parameter combinations S_j of X. This analysis requires the structuring of the tasks necessary to change a variable. This structure is related to design task modeling, where a design is divided into sub tasks. (Steward, 1981) describes the design structure matrix, a approach to managing complex design systems. (Ishii et al., 1999) provides a task modeling approach based on functional modularity. (Sreeram et al., 1998) provides a framework for task decomposition and conflict negotiation. We extend these approaches for the change cost analysis, where a change in a set of design parameter S_j requires the completion of some tasks T_k, listed in a set Q_j. These tasks are also associated with costs C^T. Therefore to change the variable combination S_j all tasks in Q_j have to be performed, creating the cost C^C_j for the variable combination S_j equal to the sum of the cost C^T of all tasks T_k in Q_j

$$\begin{aligned} Q_j &= [T_1, T_2 ... T_k ...] \\ C_j^C &= \sum C_k^T \quad \forall T_k \in Q_j \end{aligned} \qquad [14]$$

Note that the cost of changing a combination of variables is not necessarily the algebraic sum of the cost of changing each variable, as some tasks may be required for more than one changed variable. However, the cost of this task occurs only once if more than one related variable is changed. These change cost savings ΔC_j can be estimated by comparing the largest change cost at X_{2^n} for changing all design parameter with the change cost of the current design.

$$\Delta C_j = C_{2^n}^C - C_j^C \quad \forall j \in \{1...2^n\} \qquad [15]$$

It is important to be aware of the fact that the total cost of the design change is not only related to technical elements like production cost and failure quality, but also marketing plans, legal issues, available resources and supply, and other non-technical issues (Lavoie, 1979). (Martin, 1996) discusses a related issue of product variety, handling cost factors like the raw material inventory or the capacity reduction due to set ups.

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Change Time Analysis

The analysis of the time required to change one or more variables can be performed using the same method described above for change cost analysis. Here it is not the cost of the task that is investigated but rather the time needed to perform the task. To analyze the change time analysis, critical path methods or PERT techniques can be used to determine the minimum time to complete the required tasks.

(Harrison, 1997) provides a review of the critical path analysis and related techniques, including multiple examples. (Hegde et al., 1992) investigated the relation between engineering changes and time delays based on a field study. (Carrascosa et al., 1998) use the design structure matrix to estimate product development time. The approach utilized for this methodology differs from Carrascosa's approach, as the probability of change is not evaluated, but rather the change time in case a change is neccessary. Also, Carrascosa et al include factors for the level of completion of the task and the knowledge gained during this completion to estimate the new time required to complete the task.

For the change time analysis utilized in this methodology, it is assumed that each task has to be repeated completely, and no learning takes place. However, it is possible to apply other methodologies which include learning and partial repeated tasks, as for example in Carrascosa et al.

Design Trade Off

In order to create a trade off between design change cost and part cost, the cost to change the design from the optimal design X_j to the sub-optimal starting point X_{Start} would have to be known. In this methodology, it is assumed that the cost and time required to change from the sub-optimal starting point X_{Start} to the optimum for a given variable combination X_j is also the time and cost required to change the design back from X_j to the conservative starting point X_{Start}. However, this is not true for all cases, and the cost and time of a design change might differ from the cost and time to change the design back to the original state. The change time analysis can be modified to evaluate the actual time to change the design back from the optimized robust design to the error proof design.

In general, a design combination with a smaller change cost C^C_j and time Δt_j would be easier to change and more favorable for a flexible design. A trade off can now be achieved between a utility loss, ΔB_j, and the ease of changing to a more conservative design, ΔC_j. In order to evaluate a trade off it is necessary to know the likelihood of a design change for a given design X_j. In general, a change in X_j will occur if the net savings NS_j due to the change are larger than zero, i.e. the increase in monetary benefit ΔB_j outweighs the cost of change per part, depending on the production volume V. Note that the benefit ΔB_j are measured per part whereas the change cost ΔC_j is accounted for all parts.

$$NS_j = \Delta B_j - \frac{\Delta C_j}{V} \qquad [16]$$

However, the utility function to evaluate the benefits B_j uses the predicted responses, which might include inaccuracies. Depending on the prediction inaccuracies, the utility of the same design will vary. (Steele et al., 1993) demonstrated the prediction of uncertainty of experiments with small sample size based on previous experience. (Brown et al., 1998) determined experimental uncertainties in regression analysis. (Alvin et al., 1998) analyzed the uncertainty occurring in computational structural dynamics. It is necessary to determine at which level of inaccuracy the changed design will become more economic than the current design. This probability of

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design change P_j^{DC} represents the probability of the net savings NS_j due to a design change being larger than zero for a given set of changed variables *j*.

$$P_j^{DC} = P\left(NS_j > 0\right) \qquad [17]$$

This problem has to be evaluated for every single response y_i. This probability of changing for a single response y_i can be evaluated as shown below by calculating the deterministic limiting prediction error for which a design change would be beneficial. Now, the probability of the occurring error being worse than the evaluated limiting prediction error can be estimated. This prediction error is denominated as λ and is the number of deviations of the response σ_y between the prediction mean μ_y including the error offset μ_e, and the actual response as shown below. Note, that those means can also be estimated for non normal distributed responses, as can the standard deviation.

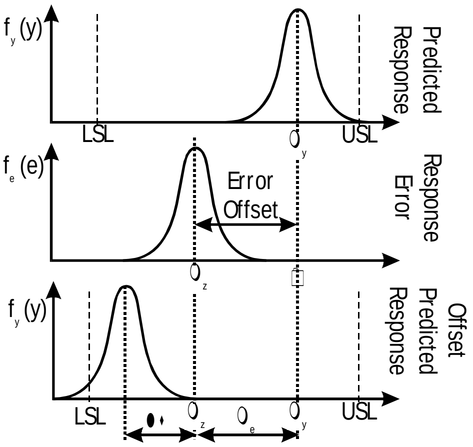

Figure 3: Error Factor

For an error factor λ_j of zero and an error offset μ_e of zero, the predicted response *y* are equal to the actual response mean μ_z, i.e. there is no error between the predicted and the actual response.

$$\mu_{z_i} = \lambda \cdot \sigma_{y_i} + \mu_{y_i} + \mu_{e_i} \qquad [18]$$

To estimate the limiting prediction error, for which a change would be beneficial, the following equation is solved for λ_j.

$$\begin{aligned} \frac{C_j}{V} = & \, U\left(\lambda_j \cdot \left[\sigma_{y_i}\right] + \left[\mu_{y_{iStart}}\right] + \left[\mu_{e_i}\right]\right) \\ & - U\left(\lambda_j \cdot \left[\sigma_{y_i}\right] + \left[\mu_{y_{ij}}\right] + \left[\mu_{e_i}\right]\right) \end{aligned} \qquad [19]$$

If the specifications are all on one side of the responses, then there will be only one solution for λ_j. However, if one or more specifications are two sided, or the specifications include both "the bigger the better" and "the smaller the better", then there may be two solutions $\lambda_{j,1}$ and $\lambda_{j,2}$. In this case, the selected error factor λ_j is the error factor closest to zero, which gives us the minimum error to justify a change from the simulated optimum towards a more conservative design.

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$$\lambda_j = \begin{cases} \lambda_{j,1} & if \ \left|\lambda_{j,1}\right| \le \left|\lambda_{j,2}\right| \\ \lambda_{j,2} & otherwise \end{cases} \qquad [20]$$

The probability of design change is equal to the probability of the net savings NS_j being smaller than zero, which is represented by the probability of the occurring error being worse than the limiting error factor λ_j. The direction of the integration depends on the closest specification limit as defined below.

$$P_{i,j}^{DC} = \begin{cases} \int_{-\infty}^{\sigma_i \cdot \lambda_{i,j}} f_e(e_i) de_i & if \ \sigma_i \cdot \lambda_{i,j} - LSL_i \le USL_i - \sigma_i \cdot \lambda_{i,j} \\ \int_{\sigma_i \cdot \lambda_{i,j}}^{\infty} f_e(e_i) de_i & otherwise \end{cases}$$

This probability P_j^{DC} for a given response y_i and a set of changed variables S_j can be determined from the distribution of the prediction error $f_e(e_i)$. This probability of change has to be determined for every response y_i in Y. With this information, the joint probability of change can be determined by multiplying the probability of no change for each response y_i with each other.

$$P_j^{DC} = \prod_{i=1}^{m} \left(1 - P_{i,j}^{DC}\right) \qquad [21]$$

Next, the trade off between the benefit loss ΔB_j and the expected savings ES_j for the selected set of changed variables S_j must be determined. Using the available information, it is possible to calculate the estimated savings per part including the probability of change. This expected savings ES_j is the probability of additional cost imposed for flexible design vs. the potential benefits of easy changes. If this expected savings ES_j per part is above zero, the design has an economic trade off.

$$ES_j = \frac{P_j^{DC} \cdot C_{s_j}}{V} - \left(1 - P_j^{DC}\right) \cdot \Delta B_j \qquad [22]$$

These trade offs have to be made between the expected savings ES and the change time t for a finite number of discrete points, therefore it is possible to compare two points and discard the less favorable one until only one design X_j remains. The recommended design is this one remaining design.

EXAMPLE: INJECTION MOLDED PART

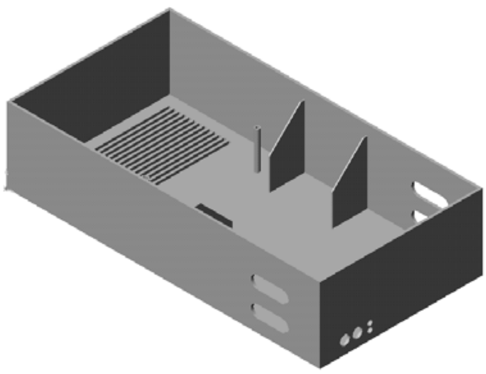

Figure 4: Injection Molding Example

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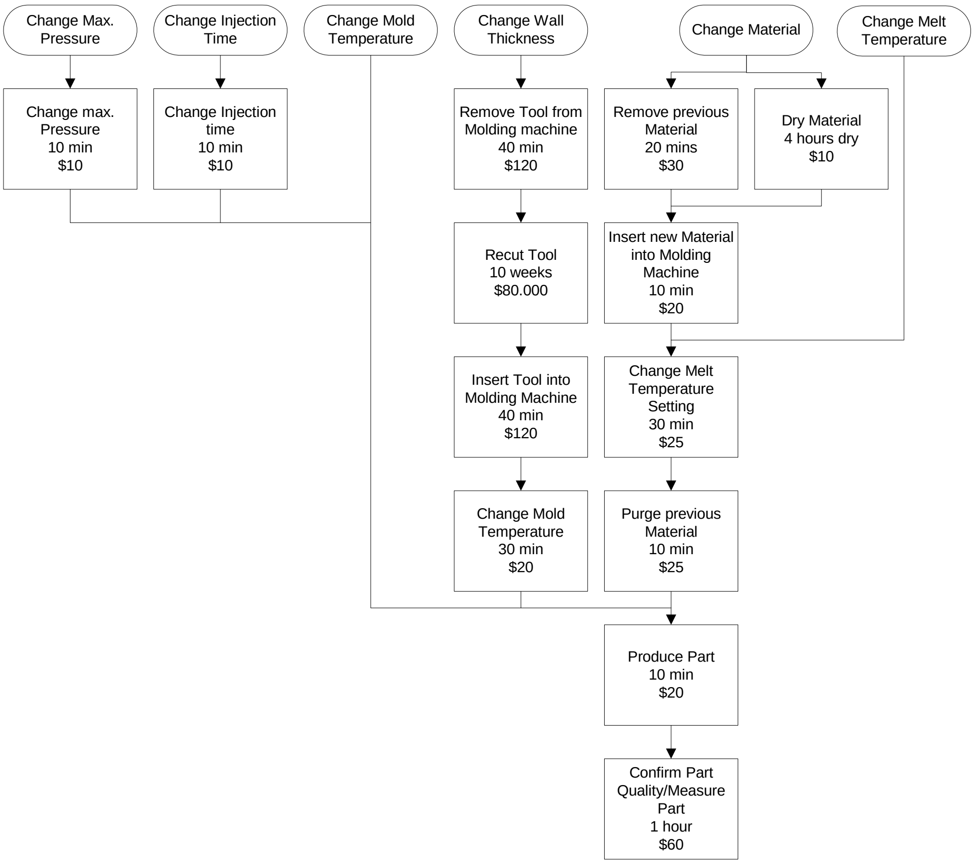

Figure 5: Design Parameter Change

The demonstrated example is an injection-molded enclosure as shown in Figure 4. Six input variables from geometry, material, and processing parameters will be modified for the design of this product. These input variables are:

- Melt Temperature
- Mold Temperature
- Injection Time
- Max. Pressure
- Molecular Weight
- Wall Thickness

In order to mold this component, a flow length of 330 mm is required. This flow length requirement might vary due to unmodeled geometry, melt temperature, mold temperature, material properties and so on. The available transfer functions will predict the flow length and the net cost of the part, based on interim predictions of the injection time, cooling time and the occurring pressure. In order to reduce the calculation time, a design of experiments was performed, generating a second order prediction equation of the response surface. In addition, an error transmission formula was applied to the prediction equations to predict the distribution of the flow length based on the distributions of the design parameters. The total cost was generated based on the cost models together with the yield of the products, i.e. the percentage of defect parts is included in the cost for one acceptable part.

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In addition, the task relations for changing one or more design variables have to be known. This relation is shown in Figure 5, where a sequence of tasks is given for each design parameter change. Note that some tasks are required for more than one design parameter change, but have to be performed only once if more than one variable is changed simultaneously. Also note that the given times and costs for the tasks are estimates and depend heavily on specific development and product characteristics. (Carrascosa et al., 1998) provides an approach to determine product development time including design changes, which can also be modified to estimate the time required to change one design parameter.

Design System and Behavior

The different product and process parameters of the system have varying effects on the flow length and the cost as shown in Figure 6 and Figure 7. It can be seen clearly that the thickness has the greatest effect on the cost and the flow length. The flow length is also affected by the melt temperature and the molecular weight of the material, whereas the mold temperature has a significant effect on the part cost through the cooling time.

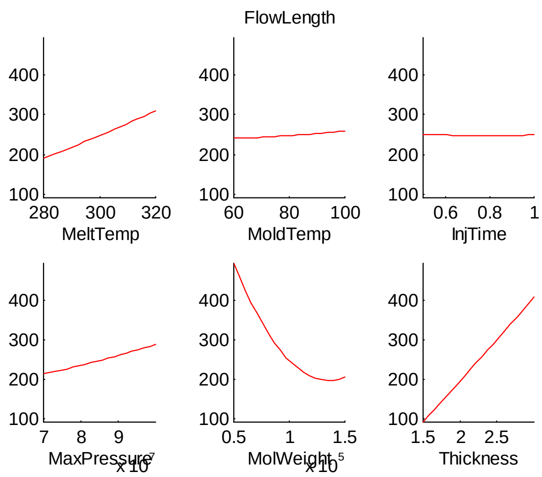

Figure 6: Relation between Input Variables and Flow Length

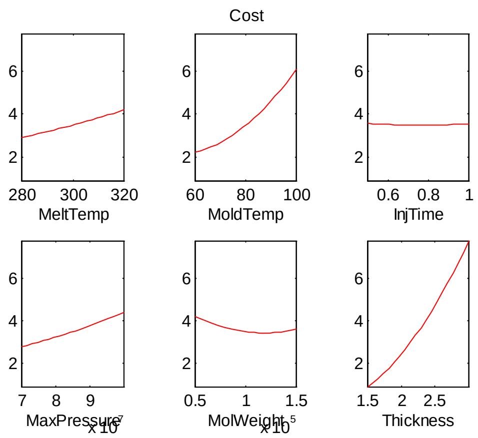

Figure 7: Relation between Input Variables and Net Cost

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Furthermore, the relation between the flow length and the pareto-optimal cost has been determined as shown in Figure 8. The thick line is the pareto optimum part cost for varying flow length and a wall thickness between 1 and 4mm if the design has unrestricted freedom to move in *X* while staying inside the design space. This line was created by optimizing the cost while constraining the flow length response to a desired value, repeating the optimization for a number of different flow lengths. Each circle represents one optimization. This line is overlaid with additional lines, which are the pareto optimal costs for varying flow lengths if the design is restricted to a discrete wall thickness. It can be seen that depending on the design, an increase in flow length may greatly increase the cost unless the wall thickness is changed, too.

For instance, a flow length of 250 mm may be achieved with a minimum cost of $1.4 per part at a wall thickness of 1mm as visualized in Figure 8. If after cutting the mold a slightly greater flow length, for example 300mm, would be required, then the minimum cost would rise to $1.5 per part. However, this would require a costly change in wall thickness in order to obtain this minimum cost. If the wall thickness remains constant at 1mm, however, the total cost would rise to $6 per part. If an increase in wall thickness was allowable, due to processing inefficiencies a possible approach would be to increase the wall thickness in order to create a more flexible design. For example, an increase of the wall thickness to 2 mm would raise the cost for a given flow length of 250mm to $1.6 per part. However, this greatly increases the design flexibility in case a larger flow length would be required.

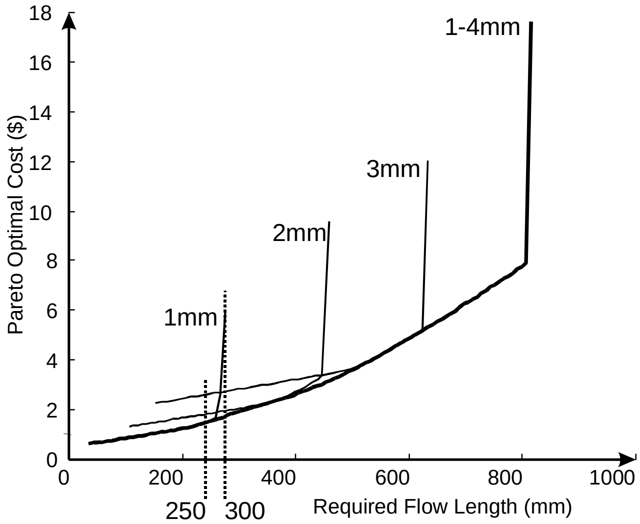

Figure 8: Pareto-Optimal Relation between Flow Length and Net Cost

Figure 9 shows the optimized relations between the flow length and the cost for changing one design parameter while holding other variables constant at the center of the design space. This is done in a similar way as Figure 8, optimizing the cost for a constrained flow length. However, this cost optimization involves only one design variable, with all other design variables remaining constant at the center of the design space. Therefore, the cost could be varied between $6 and $2 per part by changing only the mold temperature, while the influence on the flow length is only minimal. This graph also shows the pareto optimal relation between the flow length and the cost for changing all variables, which is identical with Figure 8. Depending on the variable, significant changes can be made in the cost, the flow length, or both. This graph is consistent with general practice for injection molding, i.e. in case of flow length violations, it is advisable to increase the pressure and melt temperature, and also the material might be changed. If the product was easy to mold, decreasing the mold and melt temperature might reduce the cycle time and therefore reduce the cost of the product.

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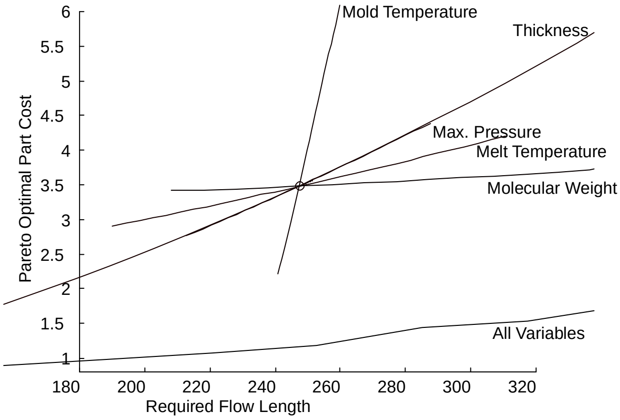

Figure 9: Design Change Flexibility

Flexible Design

The production of the example part requires a flow length of 330 mm to fill the cavity. The utilized transfer functions can predict the expected flow length mean and deviation, creating a probabilistic cost utility including the likelihood of specification satisfaction. However, the utilized models might be inaccurate, and the flow length prediction may be overestimated. Therefore, estimated prediction error distributions are used to create an error proof design by combining the noise and prediction error into the robustness criteria. The optimization of this error proof design yielded the starting point X_{Start}. However, this error proof design was less economic than some other robust designs. Therefore, the methodology was utilized to develop and analyze the possibilities to change the design from the starting point X_{Start} to a robust design with a better utility, i.e. a smaller part cost, assuming correct model predictions.

Figure 10 shows the expected savings per part ES_j vs. the change time for every set of input variable combinations, assuming a production volume of 500,000. This graph has a wide gap on the time scale between the changes involving wall thickness on the right and changes not involving wall thickness on the left. Note that although the wall thickness changes offered improvements in the part cost, they do not pay off for this example due to significant tooling costs. The expected savings range between zero and -2 cents per part, i.e. these designs may loose some money due to the high cost of changing the wall thickness for a given change probability.

A closer investigation actually revealed that the best expected savings are offered using a development strategy where only the process settings (melt temperature, mold temperature, injection time and max pressure) would have to be changed in order to reach the conservative design, with an expected savings of about \$0.0319 per parts. For the assumed 500,000 parts, this would create an expected benefit of \$16,000. Note that due to the nature of the problem, this is a theoretical number, as the decision to change the design is deterministic. Therefore either a total benefit loss of \$32,000 due to a sub optimal design is generated or, in case of a design change, \$80,500 is saved by avoiding retooling, with a probability of a design change of 40%.

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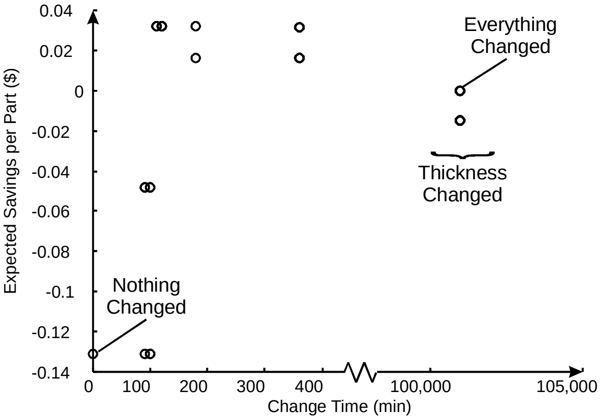

Figure 10: Expected Savings per Part vs. Change Time

However, the expected savings may differ depending on the production volume *V*. If only a few parts are produced, a design change will create much more marginal cost per part than if a large number of parts will be produced. In addition, the probability of changing a design is modified as a larger number of parts make it easier to justify a design change compared to a small production volume *V*.

SUMMARY

The proposed methodology for recommending design flexibility analyzes the available options using a rational basis, providing the developer with valuable information to solve design change problems. This approach has to be compared to the robust design approach, where the goal is to make a design robust enough so that there are no design changes necessary. However, robust design is not always successful and may result in less economic products if for example the performance predictions are inaccurate. The flexible design approach differs from the robust design approach by trying to achieve greater performance and improved utility, accepting the risk of design changes. The risk of design change is not necessarily minimized, but rather the negative effect of a design change is minimized. It has yet to be investigated if it is possible to combine the robust design methodology with the flexible design methodology, enhancing the design benefits while minimizing risk and the negative effects of risk.

The described methodology can also be used in a slightly modified version to determine the optimum design change if the obtained utility is not satisfactory. This approach was not described in this paper due to space limitations and is undergoing further development.

ACKNOWLEDGEMENTS

This research was possible with the NSF grant # 970 2797 through the Division of Design, Manufacturing and Industrial Innovation.

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