Incentives versus value in manufacturing systems: An application to high-speed milling

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A B S T R A C T

Optimal parameter selection is an important aspect of optimizing system performance. This paper examines the effect of different incentive structures, including reward and penalty based structures, for employees within an engineering firm on the value captured by that firm. Incentives are used to communicate the firm's values to the employee without revealing the firm's value function. We use a high-speed milling example to illustrate the approach and derive results. We show that, in certain cases, simple incentive structures can be aligned such that they induce profit maximizing behaviour. In other cases, we show that incentive structures result in a loss of value that we term the value gap. In the milling case considered, reward-based incentives coincide with optimal parameters while penalty-based incentives result in a greater than four-fold increase in costs. The effect of uncertainty within a system can also be analysed. We consider uncertainty in the process dynamics as well as tool life and that the inclusion of uncertainty in the analysis may not change the results in some cases.

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1. Introduction

Engineering of complex systems seeks to optimize the overall system performance. Performance requirements or specifications are often set for the components within the system to ensure proper coordination with all other components and to maximize the objective function. Recent work, however, has shown that the use of requirements can result in lost value [1,2]. Multiattribute performance targets require the specification of trade-offs among them in order to ensure normative, value-maximizing decisions [1]. Yet such trade-offs have not been implemented in practice. This paper characterizes the use of incentive structures as an alternative to the specification of trade-offs among parameters. We show that incentive systems can be aligned with system value to result in the selection of optimal system parameters.

Recent work in the management literature examines the alignment of incentives and value in decision making [3]. The motivation for examining incentives is the loss in value that occurs when incentives are improperly set [4]. Although some work has shown how to set incentives in terms of fixed targets [5] and variable targets [6,7], we have not seen related ideas in the context of engineering

systems. This paper integrates incentives structures and engineering and shows that in some cases, it is possible to obtain optimal parameter selection through simple incentive structures.

We examine how different incentive structures affect the overall system value. Rarely does an engineering system operate independently of human interaction, and people's actions and decisions are influenced by the incentives they face. If these incentives are poorly constructed, it is possible that the actions of people will hinder the performance of the system. In a manufacturing firm, for example, the complex system represented by the factory and the manufacturing equipment can be optimized to maximize the profit for the firm. However, if the incentives in place for employees subvert the system, then the firm will lose value. Understanding how incentives may affect employee behaviour and decisions is of great importance. Even in firms that do not offer explicit incentives, implicit incentives arise in a variety of settings [8,9]. Thus, we are compelled to examine incentives and whether they can be set to ensure optimal system performance and value capture.

In order to understand how incentives affect the value, we first must determine the optimal value capture for a given system through a value-based optimization problem. In this case, we assume optimal behaviour and decisions from all people. Next, incentive structures are introduced that influence the decisions made by employees. Multiple types of incentive structures are studied. For each case, the effect on system value is quantified.

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The analysis is formulated in the context of a high-speed machining example. High-speed milling involves the selection of numerous manufacturing parameters by the machinist who operates the manufacturing equipment and/or the programmer who writes the numerical control instructions for the machine tool. We consider how incentives may affect these decisions given the machinist's discretion in the manufacturing process and ability to influence the system in a variety of ways, keeping in mind that software exists to support milling parameter selection. Any decision support available from software serves to support the use of optimal response to the incentive structure in the model. The purpose of this context is to provide a simple, but real life engineering example that examines how incentives affect system value. Previous work in milling has examined the effect of uncertainties on the milling parameter decisions [3,10], but the effects of incentives have not yet been studied.

We examine incentives at the individual employee level. Extensive economics literature on incentive structures exists. The effect of incentives on behaviour is complex, but the literature is in agreement that incentives do affect behaviour [11,12]. Work in this area has studied the psychology of incentives and how they affect employee effort and motivation [13]. The interaction of incentives and task complexity, employee skill, and employee personality has also been studied [14].

Incentives can be structured as rewards or penalties. Empirical studies show employees generally prefer incentives framed as rewards [15,16]. A common type of reward based incentive is known as the piece rate incentive in which the employee is paid a bonus for each additional unit produced [17]. Empirical evidence has shown that piece rate incentives can increase productivity [18]. Other work has shown, however, that when information and actions can be hidden, no incentive structure can induce optimal behaviour [19].

This work is also related to the literature that describes human system interaction [20]. The focus is generally on humans as end users of systems and issues such as the usability are considered [21]. This approach contrasts with ours in that we treat the human or employee not as an end user, but rather as an integral component that functions within a larger system. Our treatment of the role of humans within a system's function is related to work on the use of aids for decision making in systems [22,23].

The remainder of this paper is organized as follows. Section 2 describes the machine setting during milling for which the analysis is completed. Section 3 presents the analysis and results for a deterministic case while Section 4 incorporates uncertainty in the system. Section 5 discusses the results, and Section 6 provides concluding remarks.

2. High-speed milling in engineering systems

We examine incentives within a high-speed milling application. High-speed machining entails the use milling at very high speeds to systematically and quickly remove metal from a base surface or workpiece, thereby producing a product with geometry significantly different from the original piece. In milling, several decision parameters must be determined for a particular project. Due to the large number of decision parameters and their complex effects on outcomes, the optimal choice of parameters can be modelled as a system design problem with a known value function. A full description of the decision parameters has been discussed in the literature [3]. We present an overview with attention to those aspects most important to our analysis.

The decision variables in milling can be categorized into three groups: tool parameters, holder/machine parameters, and milling parameters. The tool parameters describe technical aspects of the
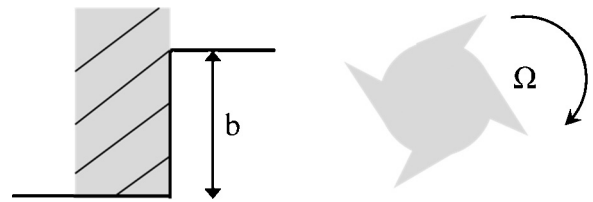

Fig. 1. The axial depth of cut (b) is the commanded depth of cut along the tool axis. Spindle speed (Ω) is measured in rotations per unit time.

tool, such as its material/coating, geometry, diameter, and number of teeth. The holder/machine parameters describe the holder material, geometry, and the tool insertion length into the holder, as well as the machine and spindle into which the holder-tool will be clamped. Milling parameters include the rotating speed of the spindle and the axial depth of cut as illustrated in Fig. 1. We will assume that the radial depth of cut and feed per tooth are fixed parameters.

The properties of the tool and holder/machine determine the process dynamics, which affect the cutting forces and tool vibration. We treat the process dynamics as deterministic for a given tool and holder/machine selection. These dynamics determine the stability of the milling system. When the system is unstable (i.e., self-excited vibrations, or chatter, are present), a low quality product is produced that is either worthless to the manufacturer or requires significant rework to make it acceptable. Thus, the process dynamics determine the stability limit, or the boundary that identifies the maximum axial depth of cut for which the process is stable at the selected spindle speed.

The milling parameters subsequently affect the cost of milling. The allowable axial depth of cut partially defines the tool path which affects the time to complete a task. Both the depth of cut and the spindle speed influence the tool life. The effects of all decision parameters are illustrated in Fig. 2 where double ovals represent deterministic calculations, rectangles represent decisions, and the hexagon is a value node.
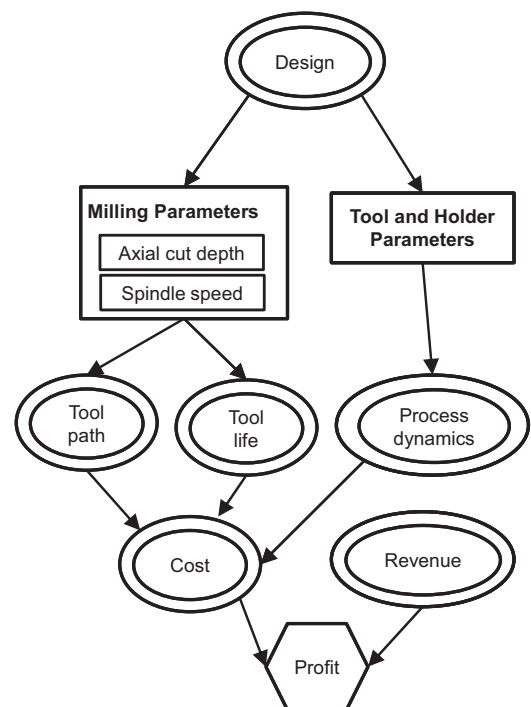

Fig. 2. The selection of the milling, tool, and holder parameters determine the overall profit as illustrated in the high-speed milling decision diagram.

For the numerical analysis in this paper, we consider a single choice of tool and holder, a TiAlN-coated, tungsten carbide endmill (10 mm diameter d, 4 teeth) that is used to machine SKD61 steel. We consider the task of machining away a cube of steel with an edge length of 100 mm. We consider a simplified scenario in which some of the parameters are fixed. With the geometry of this milling task, we can determine the tool path for machining the cube and use this to determine the actual cutting time to remove the cube of material, t_c, as well as the total time to machine the cube, t_m,

$$t_c = \frac{W}{b\Omega f_t N}\left[\frac{W}{a}(W + d)\right] \tag{1}$$

$$t_m = \frac{W}{b\Omega f_t N}\left[\frac{2W}{a}(W + d) + W\right], \tag{2}$$

where d is the tool diameter, W is the length of the cube edge, N is the number of teeth, f_t is the feed per tooth, and a is the radial depth of cut. We refer the reader to Abbas et al. for a full explanation of f_t and a [3]. In this analysis, these values are held fixed at 0.15 mm and 3.0 mm, respectively. Note that the time spent cutting (t_c) is less than the total time to machine the cube (t_m) due to time needed to reposition the tool between cuts. Both times are determined by computer aided design/computer aided manufacturing (CAD/CAM) software that determines the tool path required to produce the desired geometry.

Both the tool selection and the milling parameters affect the tool life. A Taylor-type tool life equation is used to determine tool life, where the constants are determined by the tool choice and workpiece material [3,24,25]. The tool life T, or the time required to reach a predetermined wear level on the cutting edge, for the case used in this paper is given by the following equation

$$T = 2.3741 \times 10^6 b^{-0.2837}\left(\frac{\pi d\Omega}{1000}\right)^{-1.6265}. \tag{3}$$

The cost for milling, C_m, is then calculated as

$$C_m = t_m r_m + (t_{ch} r_m + C_t)\frac{t_c}{T} \tag{4}$$

where r_m is the cost per minute for milling, t_{ch} is the time in minutes to change a worn tool, and C_t is the cost per tool. In this example, r_m is \$1/min, t_{ch} is 0.07 min, and C_t is \$114.

The objective of a for-profit engineering firm is to maximize profit, P. In addition to the costs of milling, some fixed costs, C_f, may exist. We treat the revenue, R, from the product as deterministic, which may be the case for a firm that works on a contract basis to manufacture fully specified products. The objective for the firm is then to maximize P,

$$P = R - C_m - C_f. \tag{5}$$

We omit fixed costs from our analysis without affecting the results.

Finally, the optimization must consider the stability boundary imposed by the process dynamics. The approach for determining the boundaries for both the deterministic and the uncertain case is described in the literature [26]. The boundary for the deterministic numerical example we use is presented in Fig. 3. Incorporating uncertainty is discussed in Section 4.

3. Deterministic analysis and results

The central motivation for this analysis is the possibility that incentives can affect the overall system value to a firm. In the case that incentives induce behaviour or decisions that negatively impact profit, we define a measure known as the value gap. Let the optimal profit obtainable be denoted P^*. The profit obtained
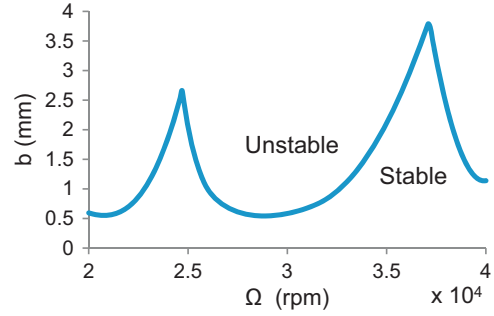

Fig. 3. The process dynamics constraint imposes a boundary on the stable operating region.

with incentive structure i is denoted P^i. The value gap is then the difference,

$$\text{Value gap} = P* - P^i. \tag{6}$$

A strictly value based approach is an optimization over the profit function. It is assumed that all employees will operate consistently at the optimal values in the absence of any incentive structure.

For the high-speed milling case, Eq. (4) describes the cost of milling, C_m, in terms of spindle speed, Ω, and axial depth, b. We have assumed the revenue will be constant. Therefore, maximizing profit is equivalent to minimizing C_m. The minimization occurs over the domain defined by the stability boundary illustrated in Fig. 3. If milling occurs in the unstable region, then chatter occurs that causes the tool to wear out faster and the cost to increase; we therefore do not consider this region We find that P^* occurs at the point (b, Ω) = [3.80, 37, 100] with a minimum cost of \$38.43 per unit milled. Fig. 4 shows the cost as a function of spindle speed where the limiting axial depth is used for each spindle speed. The limiting axial depth is the axial depth along the stability boundary.

We examine the effect of incentives for the machinists on the optimal profit, or minimum machining cost, for the firm. This analysis assumes that employees adhere to the rules of normative decision making [27], and their decisions are influenced by incentives. We present three cases: penalty based incentives, reward based incentives, and a hybrid incentive structure.

3.1. Penalty based incentives

We first consider the case where the incentive structure is formulated as a penalty. The high-speed milling firm incurs additional cost for each tool that wears out. The rate at which the tool wears out is determined by the milling parameters chosen by the machinist. We consider the case where the firm pays employees an hourly wage and imposes a penalty for each tool the employee wears out. The machinist's objective is therefore to maximize the tool life, T.
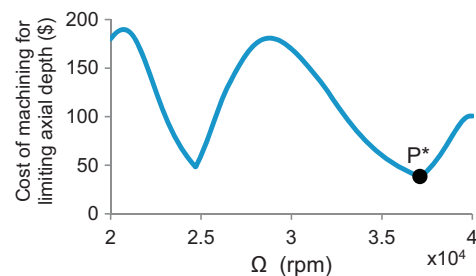

Fig. 4. The cost as a function of spindle speed where the limiting axial depth is used for each spindle speed.
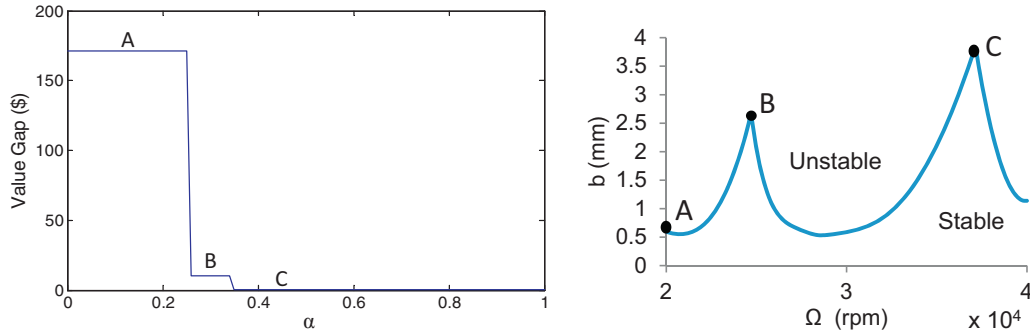
Fig. 5. The value gap takes on three different values as the mix of reward and penalty in the incentive changes that correspond to points on the stability boundary.

A trivial solution in this case is for the employee to stop working because this will ensure that no tools wear out. We therefore impose the restriction that the machinist must operate continuously and maintain parameters within the domain $b \in [0.5, 4\,\text{mm}]$ and $\Omega \in [20,000, 40,000\,\text{rpm}]$. These assumptions are consistent with the case in which a supervisor oversees the machinist's work. In this case, the maximum T occurs at $(b, \Omega) = (0.5, 20,000)$. The cost is \$209.72 per unit, resulting in a value gap of \$171.29.

The optimal solution for the machinist in the penalty case is to operate at the minimum bound set for both axial depth and spindle speed. The value gap is thus determined by the minimum bounds selected.

3.2. Reward based incentives

We next consider the case where the incentives are structured as rewards. The machinist is paid a bonus for each part that is produced. In this case the machinist's objective is to minimize the time spent milling the product, t_m. The best values for the machinist are $(b, \Omega) = (3.79, 37,100)$, yielding a cost of \$38.43. This cost matches the optimal case and results in a value gap of \$0.

3.3. Hybrid incentive structure

We next consider the case where the machinist receives both a reward for each unit produced and penalty for each tool that wears out. We consider the case of a convex combination of reward and penalty,

$$I = \frac{\alpha}{t_m} - \frac{(1 - \alpha)}{T} \tag{7}$$

where α is a parameter that governs the amount of reward or penalty and I is the total incentive pay to the machinist. The reward is based on the number of units produced. The penalty is based on the number of tools that wear out. I can be positive or negative.

The machinist's objective is to maximize I. The value gap as a function of α is a step function as shown in Fig. 5. The value gap is \$171.29 for $0 \leq \alpha \leq 0.25$, \$10.01 for $0.26 \leq \alpha \leq 0.34$, and \$0 for $\alpha \geq 0.35$. These steps are labelled A, B, and C, and the corresponding points in the stability diagram are also shown in Fig. 5. Note that we also impose domain restrictions of $b \in [0.5, 4\,\text{mm}]$ and $\Omega \in [20,000, 40,000\,\text{rpm}]$ which affect the first step of the value gap.
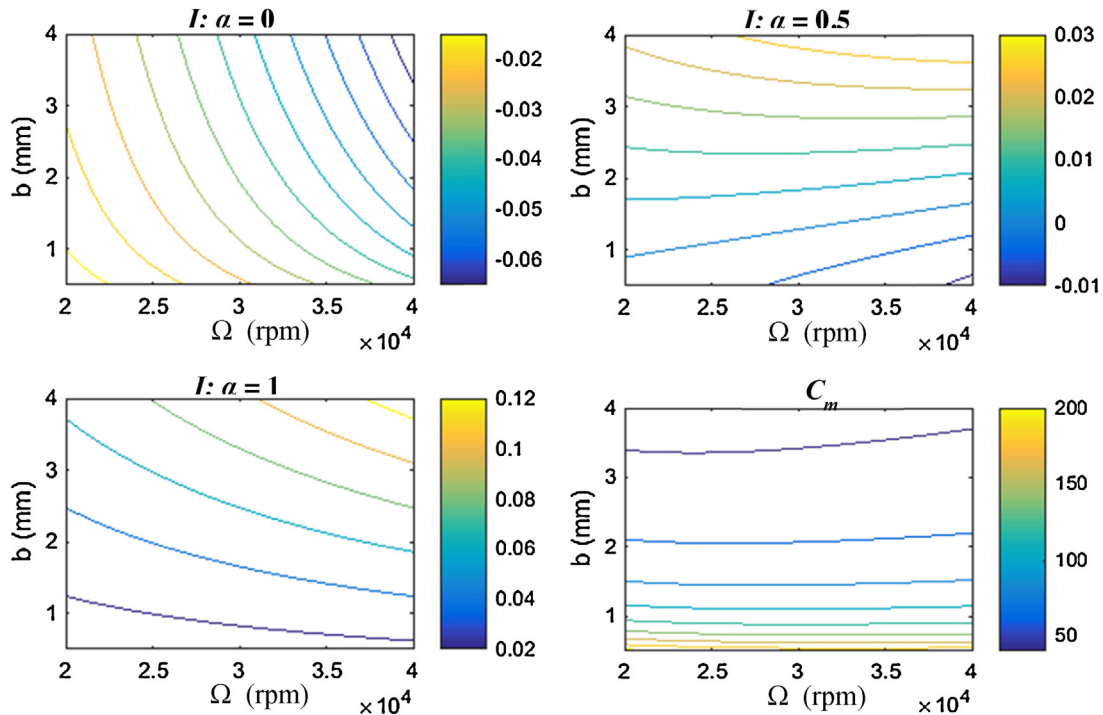

Fig. 6. The contours of the hybrid incentive illustrate how the parameter α affects the machinist's trade-offs between the variables and the level of congruence between the hybrid incentive and the cost of milling.
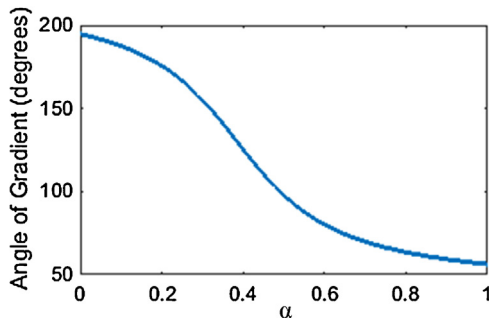
Fig. 7. The gradient of the hybrid incentive at the point $(b, \Omega) = (2.50, 37500)$ as a function of the parameter α.

Fig. 8. Uncertainty in the process dynamics constraints is shown by the low, base, and high fractiles.

The parameter α governs how the machinist values trade-offs between the decision variables. The change in trade-offs can be illustrated by plotting the surface contours for different values of α as shown in Fig. 6. When maximizing the hybrid incentive, the direction of the maximization with respect to the decision variables changes significantly as the parameter α changes; Fig. 7 underscores this result by showing how the gradient of the incentive changes as a function of α at a given point. These changes may be compared to the contours of the cost of milling, also shown in Fig. 6. Although none of the incentive surfaces matches the cost surface, because the directions of the gradients are similar and because the system has nonlinear boundaries, the result of optimizing over these two difference surfaces is the same set of optimal parameters for a wide range of α values.

4. Incorporating uncertainty

In practice, not all the relevant parameters are known deterministically; some uncertainty is present. This uncertainty may arise from numerous sources including the stability boundaries [3] and the actual tool wear [32].

4.1. Uncertainty in stability boundaries

In high-speed milling, the process dynamics include the characterization of forces that exist between the tool and the work piece. These forces are described by a cutting force model. These forces may be uncertain, leading to uncertainty in the force model coefficients. Uncertainty in these coefficients in turn creates uncertainty in the process dynamics constraints. We consider the effect of this uncertainty on the value gap induced by incentives.

We use classic probability encoding techniques to describe the uncertainty in the force model coefficients. We discretize the probability distribution into three fractiles of the cumulative distribution: the 10%, 50%, and 90% fractiles. Each fractile has an
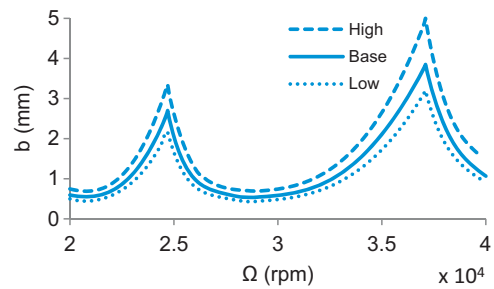
associated variable: X_{Low}, X_{Base}, and X_{High}, respectively. The probability mass function assigned to these variables is $\{0.25, 0.50, 0.25\}$. We use expert elicitation to determine the values for this case study, and refer the reader to previous work for a complete description of the process [3]. Additional information on probability encoding and constructing probability distributions is available in the literature [28–31].

The uncertain force model coefficients were used to calculate the associated stability boundaries as presented in Fig. 8. We repeat the analysis of the hybrid incentive structure using these boundaries. We assume the stability boundaries are uncertain when the manufacturing firm sets the incentive, and the machinist is able to observe the actual stability boundary when selecting the spindle speed and axial depth.

We use the minimum cost for each stability boundary to find the value gap for that boundary as a function of the incentive parameter α as shown in Fig. 9. The overall expected value gap is a weighted average of these step functions and is also shown in Fig. 9. The expected value gap is $0 for $0.37 \leq \alpha$.

4.2. Generalized uncertainty in the system

Any uncertainty that exists in the system also exists in the incentive structure. Thus, the incentive based approach can be used for non-deterministic systems. For example, if the tool life is uncertain, then this uncertainty translates to uncertainty over the costs as well as the incentive. To analyse the system under conditions of uncertainty, the uncertainty must be translated from a distribution over the parameter to a distribution over the objective function. In this case, the analysis requires the calculation of the distribution over the cost and the incentive.

To illustrate the inclusion of uncertainty, we consider uncertainty in the tool life. We use (3) as the midpoint of a uniform distribution. For example, suppose there were $\pm 2\%$ error in the estimation of tool life. The distribution over tool life is then represented as a uniform distribution on the range $(0.98\,T, 1.02\,T)$ to
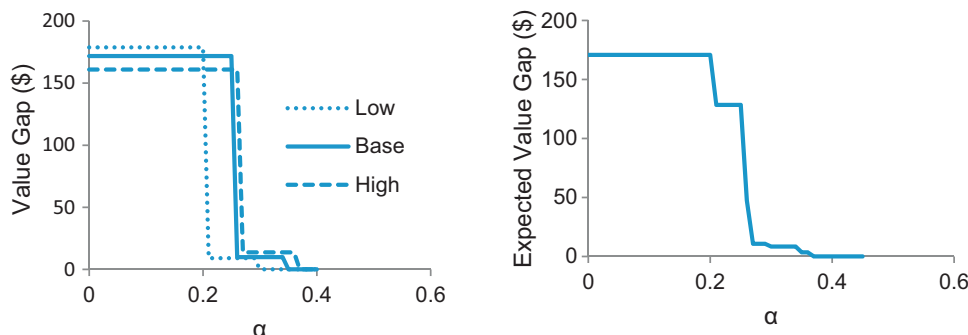

Fig. 9. The low, base, and high fractiles of the value gap and the overall expected value gap.
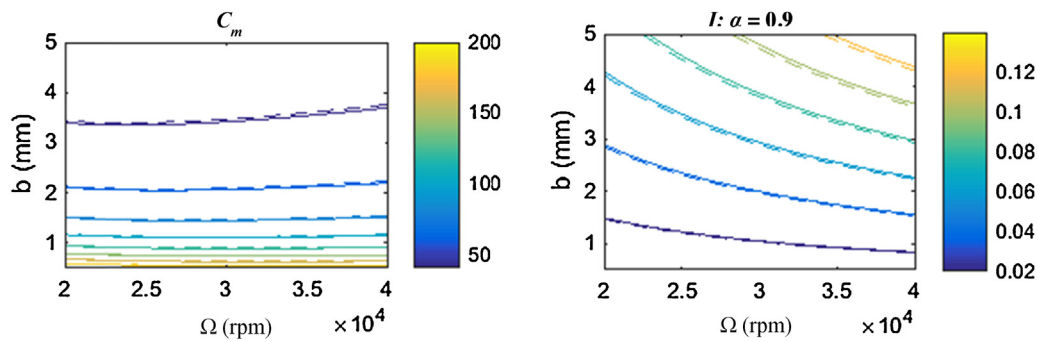
Fig. 10. The inclusion of uncertainty (dashed lines) in parameters results in small shifts from the deterministic case (solid lines).
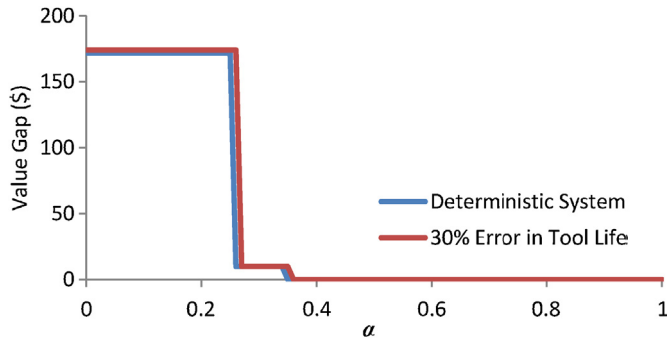

Fig. 11. The difference in value gaps as a function of the hybrid incentive parameter α

represent maximum entropy within the range. We then vary the width of that distribution to determine the sensitivity of the results to uncertainty. When comparing the expected value of the objective function to the value in the deterministic system, we see very little variation. For example, Fig. 10 shows the difference in contours when the tool life is deterministic (solid lines) and when the tool life has ±20% error. Small differences are observed even in this extreme case of error that is well beyond the error that exists in current tool life forecasting methods [32].

We analyse the effect of uncertainty on the optimal hybrid incentive parameter α. We find that the shape of the resulting value gaps closely match the results of the deterministic case in Fig. 5. Only as the error in tool life becomes drastic do the selected parameters change. Fig. 11 compares the deterministic case to the results of ±30% error in tool life. Even in this extreme case, the α values increase by 0.01 at which the selected parameters change. This level of error is well beyond what would be expected in practice.

5. Discussion

We have analysed the effect of three incentive structures. The hybrid incentive structure provides insight into the reward and penalty structures because it is a generalized case of the two. When $\alpha = 0$, the hybrid incentive simplifies to the penalty-only case. When $\alpha = 1$, the hybrid incentive represents the reward-only case. The results for the hybrid incentive at these values of α match the results in the penalty and reward structures.

In the penalty-only case, the results are sensitive to the minima set for the domains of b and Ω. This sensitivity results from the existence of a trivial optimal solution: do nothing. The optimal parameters therefore take on their respective minimum values due to the emphasis on tool wear.

The results of the reward-only and hybrid incentive showed it is possible to obtain a \$0 value gap through incentives. Given that the reward-only incentive is a special case of the hybrid, these results

compel careful consideration of the construction of the hybrid incentive. This incentive (7) is based on the machining time (t_m) and the tool life (T), variables that also appear in the cost function (4). Not only do the same variables appear, but they affect the two functions in similar ways: increases in t_m are detrimental to both while increases in T are beneficial to both. By formulating the hybrid incentive as a convex combination of these opposing forces governed by the parameter α, it is possible to effect large changes in the gradient of the hybrid incentive simply by changing α.

The results show a wide range of values for α result in optimal parameter selection. This result, however, is sensitive to the active boundary constraints of the system. In our milling example, the process dynamics constraint is the active constraint in the system optimization. The optimal parameters occur at a discontinuity in the constraint. Because of this discontinuity, a wide range of gradient angles for maximizing the hybrid incentive correspond to the same optima as minimizing the cost. This result illustrates that it is possible for simple objective functions to result in the same optimal parameter selections as more complex value functions.

We also examined the effect of uncertainty in the system. Interestingly, the analysis shows similar results for the deterministic and stochastic cases. When considering uncertainty in the process dynamics constraints, the reward-only results are unchanged. For a hybrid incentive, the critical value of α above which the value gap is \$0 increases due to the effects of the different and uncertain boundaries. The overall effect of α, however, is consistent with the deterministic case; as α increases towards the rewards-only case, the expected value gap decreases. When considering uncertainty in tool life, very little change is observed in the behaviour of the value gap. These results provide evidence supporting the robustness of incentive-based parameter selections to the presence of uncertainty. This robustness results due to the same source of uncertainty for both the cost function and the incentive function.

The results in this paper show that in some cases, it is possible to communicate values and acceptable trade-offs among parameters using simple functions and still obtain optimal results. Thus, in systems operating with multiattribute performance requirements, it may be possible to use simplified trade-offs among the requirements to facilitate the optimization without sacrificing performance. These findings are also important for engineering firms wishing to maintain the confidentiality of information while communicating trade-offs to engineers.

The results of this paper also illustrate the importance of understanding the effect of incentive structures within the context of systems engineering. Poorly aligned incentive structures may cause significant loss of value. In some cases, such as the high-speed milling example we analyse, it is possible to create incentives that are both simple and that induce value-maximizing behaviour. These results underscore the potential for using incentive structures to maximize value in engineering firms.

6. Conclusion

The literature describes the effect of incentives on effort and motivation on manufacturing, most notably through the use of piece-rate incentives. Motivated by the positive psychological effects of incentives, this paper examines the effect of incentive structures in manufacturing decisions and parameter selection within engineering systems. We use a high-speed milling example to illustrate the approach. We analysed three different incentive structures: reward based, penalty based, and a hybrid structure. The hybrid incentive constructed in the example allows for system optimization over a variety of trade-offs among the decision variables as shown by the range of gradient angles obtainable. We find that both the hybrid and the reward based incentives induce value maximizing decisions and that these results are robust to the inclusion of uncertainty in the system. Thus, we show that values and acceptable trade-offs among variables can be communicated using simple incentive functions. This result facilitates the use of normative multiattribute requirements with trade-offs and also has the potential benefit of facilitating the maintenance of proprietary value function information. These results also indicate the importance of understanding the dynamics of the system to which incentives are applied.

This work introduces a new approach to supporting parameter selection in engineering systems. Much work has studied the effect of incentives on effort, but this paper is the first to show that incentives may also support optimal decision making. On the basis of these results, future work is needed to verify the approach in other engineering systems and to study the possible synergistic effects of incentives that positively affect both effort and decision making.

Acknowledgements

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