Component replacement under uncertainty – a switching option perspective

Gianluca Fusai[a,b,*], Ioannis Kyriakou[b], Matteo Castiglioni[a]

[a] *Dipartimento di Studi per l'Economia e l'Impresa, Università del Piemonte Orientale, Via Perrone 18, 28100 Novara, Italy*
[b] *Cass Business School, City, University of London, 106 Bunhill Row, London EC1Y 8TZ, UK*

Abstract

We develop a novel, workable switching option model approach to component redesign and replacement projects that are divisible into sequential phases. The component manufacturer has the option to retain the current product position and abandon the project, or switch to a redesigned product position. Additional uncertainty remains as to whether the redesigned product can meet the newly set production efficiency criteria. Depending on the viability of a prototype, the firm can finally decide whether or not to move to final production. Our framework incorporates a potentially valuable option which aims to reduce the cost of the project. It is generally applicable to fields where investments in components' replacement have to be correctly timed due to large costs and uncertainties about the outcome. We illustrate this by means of a case study application in aeronautical engineering using real data, where we show via a sensitivity analysis based on the key variables that the flexibility of component switching offered via options during the development of the project can be significantly valuable.

Keywords: Component replacement, uncertainty, switching option, cost-effectiveness analysis

1. Introduction

Innovation and incremental improvements of the design of a product or a system are crucial for its performance, especially for long life cycles, as in the aerospace sector. Investments in design projects can be divided into sequential phases, giving the firm the opportunity to change the way the project evolves. In this paper, we focus on a component switching project for a system and investigate whether this is worth undertaking, i.e., if it can reduce the expected costing of the replacement parts. The workability of our proposed project valuation approach

[*] Correspondence
Email addresses: gianluca.fusai.1@city.ac.uk & gianluca.fusai@uniupo.it (Gianluca Fusai), ioannis.kyriakou@city.ac.uk (Ioannis Kyriakou), 2026860@studenti.uniupo.it (Matteo Castiglioni)

is elucidated by a case study from aeronautics, where we explore component replacement for a rotorcraft, that is, our system, using real data, and can appeal leading providers of maintenance, repair, and overhaul (MRO) services for aircrafts, engines and components. Besides, the recent years have seen a considerable annual growth rate in the MRO and auto parts remanufacturing industries (e.g., see Vlaanderen, 2018, Shi *et al.*, 2020).

Our research pertains to the domains of production flexibility and real options. Production flexibility enables the manufacturer to limit the downside risk of operations by curtailing down production while tapping on favourable upside potentials (see Chevalier-Roignant *et al.*, 2019). We view production flexibility as a switching option between different production positions. Real options – a term coined by Myers (1977) – analysis (ROA) allows the quantification of the firm's flexibility to estimate the value of production flexibility under uncertainty (see, e.g., Dixit and Pindyck, 1994, Smith and Nau, 1995, Trigeorgis, 2007). This is facilitated by assimilating financial option theory to investment decisions made by firms. ROA takes into account the uncertainty in the cost-to-completion of the project, the uncertainty in the cash flows to be generated from the project, and the possibility of fatal events that may put an end to the effort before completion. The use of the ROA to define the timing of the replacement of a component helps firms evaluate and structure strategic investment opportunities under uncertainty.

A type of investment choice that fits in well with the RO logic is Research and Development (R&D) (e.g., see Paxson, 2001) and high-technology investment decisions (see Angelis *et al.*, 2014), where decisions are taken under a high level of uncertainty. Some case studies inspired by real investment decisions underline the benefits of ROA for strategic decision-making (see Trigeorgis and Reuer, 2016) and demonstrate the range of applicability of ROA (see Anderson, 2000). With a focus on the aerospace maintenance, repair, and overhaul industry, Miller and Park (2005) present a real-data application of their real options methodology for guiding a multi-phased irreversible investment decision involving process design and capacity planning decisions. In capital-intensive industries, such as in the petroleum industry (Lopes *et al.*, 2019) and in the development of natural resource reserves (Smith and McCardle, 1999), which are at ease with capital budgeting decision tools, real options are evaluated in combination with decision analysis approaches. Related to the real options literature that deals with applications in commodity and energy industries is also the work of Secomandi and Wang (2012) who consider network contracts for natural gas pipeline transport capacity, whereas Enders *et al.* (2010) look into the interaction between the option to scale the level of natural gas production level and the option to scale the extraction rate. Secomandi and Seppi (2014) focus on industrial facilities responsible for the transformation processes of commodities (conversion assets), which can be seen as real options on the prices of the underlying commodities. Other examples can be found in the electricity, pharmaceutical and biotech industries (e.g., see Magazzini *et al.*, 2015 and Chambers *et al.*, 2009), but also in operations management in manufacturing and power generation, especially in capacity planning and the evaluation of operating flexibility (as in Rębiasz *et al.*, 2017 and Jiao *et al.*, 2007). All these cases involve significant upfront investments that often do not lead to immediate cash flows. They also tend to have well-defined stages with major sources of uncertainty whose resolution is expected to contribute significantly to the outcome and ultimate value of the projects (see Triantis, 2005). Flexible decision structure is relevant in manufacturing operations management (see Huchzermeier and Cohen, 1996, Kume and Fujiwara, 2018 and Nembhard *et al.*, 2000) or in project scheduling, where the timing decision to start a new product development is influenced by input-cost fluctuations (see Fisch and Ross, 2014). There might be uncertainty about the project arrival, the processing time, or the required resource capacity for the project, etc. When scheduling such an uncertain project, project management might await additional future information before rescheduling (see Boute *et al.*, 2004).

The model framework presented in this paper is a compelling switching option application to a redesign project. We divide into sequential stages giving the manufacturer the option to change the evolution of the project or even abandon it during the development period based on an evaluation of the state of the project at each stage. Whilst we focus on a redesign component project in aeronautics as part of our illustration, this is certainly not restrictive as the proposed approach can be adapted to other fields where investments in components' replacement have to be correctly timed due to large costs and uncertainties about the outcome from the introduction of new technologies not fully exerted by the company. The model comprises three phases. The design team may either select a product position that translates into the current technology, or switch its product position in order to avail of upgrades in technology; Jain and Ramdas (2005) call this the pace-keeping approach. Additional uncertainty remains as to whether a specific firm's prototype will meet these hurdles. The firm then needs to develop a prototype and decide whether it meets, for example, the customers' feedback and certain production efficiency criteria. Depending on the viability of the prototype, the firm can finally decide whether or not to commercialize this and launch the new product category.

The choice between continuing with a replacement of components and abandoning the project constitutes a potentially valuable option which is aimed to reduce the cost of the project. To this end, we first use data comprising real replacement times and the corresponding numbers of replaced components to estimate analytically the probability distribution of the replacement time and the number of replacements. Based on this, we then build the cost-effectiveness likelihood of our switching option redesign strategy against continuation of the current component production. We study the effect of key variables in the aforementioned phases, including number of systems sold, fixed costs involved and probabilities of successfully passing the different phases. Overall, we find that the number of systems sold plays a primary role in the cost discrepancy between the original and the redesign project. In line with current market parameter values, our model yields 90% chance of cost-effectiveness brought by redesign, which can further grow given the projected increases in the number of systems sold in the short to medium term, as well as stochastic dominance by first order over the current production. In addition, our model has been able to hold out satisfactorily against adversely extremely stressed parameters, such as phase success probabilities and fixed costs, yielding a profitable redesign project with more than 50% chance.

The remainder of the paper is organized as follows. In Section 2, we present our switching option model approach to component replacement. Section 3 introduces our case study application in the aeronautical industry. In Section 4, we describe the implementation of our framework to the aforementioned case study and proceed with it using real replacement times of components. In Section 5, we perform project valuation accompanied by an appropriate cost-effective analysis based on the key inputs and examine the degree of stochastic dominance between the current and redesign strategy. Section 6 concludes the paper.

1.1. Stochastic dominance in the component replacement problem

2. A switching option model for component substitution

In the aerospace industry, where the life cycle of an aircraft is very long, typically exceeding 40 years, the continuous improvement in design and the introduction of new versions of the product are necessary to remain competitive. These are typical R&D investments that require large initial amounts of capital, with profits only to be recovered long after. Management of the early phases of a project, such as concept generation, preliminary design and product planning, is of utmost importance for a successful product innovation. In addition, any corrective action and engineering change results in considerable cost and time increases as the project implementation progresses. During early phase, managers and decision makers face maximum uncertainty about the constraints and opportunities in the product life cycle.

R&D investments can be generally divided into sequential phases or staged paths, so that the firm acquires the opportunity to change the evolution of the project during the development period. More specifically, the design process can be modelled as an option to continue, change path or abandon the project following an evaluation of the state of the project in each sequential phase. Here, we study a redesign component project and propose a way of evaluating it by dividing the total investment into sequential premiums paid to establish options that will offer potential switching routes in the project implementation. The choice between continuing and abandoning the project, if conditions turn out to be unfavourable, constitutes a potentially valuable option as, by truncating poor outcomes, it is hoped to yield the expected project value increases. Our ultimate goal is to determine whether the redesign project is indeed lucrative for the company.

2.1. Model framework

We define the random number of replacements N_0 of the current component

$$N_0 = \max\left\{n\colon \sum_{i=1}^{n-1} \tau_i^0 \leq H\right\}, \quad H_{l,0} \leq \tau_i^0 \leq H_{u,0}, \tag{1}$$

where H is a system's life, $\{\tau_i^0\}_i$ is the collection of independent and identically distributed (i.i.d.) random lengths of the component replacement periods (in number of whole hours), and $H_{l,0}$ and $H_{u,0}$, respectively, its lower and upper bounds. More specifically, $H_{u,0}$ denotes the component's fatigue life limitation, i.e., the range of its capability to withstand the operating loads without failures during the service life of the system. The use of such a maximum is essential for safety reasons. $H_{l,0} > 0$ is the minimum lapse of time until the first replacement duration and this is practically nonzero to allow for inspection for defects, damages or failures.

In the following proposition, without loss of generality, we assume that τ_i^0 has a discrete probability distribution taking equally spaced distinct values from $H_{l,0}$ to $H_{u,0} = \alpha H_{l,0}$, where $\alpha \in \mathbb{Z}^+$, in consistency with current inspection cadence in practice, however this can be easily adapted, for example, to a continuous distribution for the time, if needed, depending on the nature of a given study.

Proposition 1. *Under general assumptions for the probability distribution of* τ_i^0*, the probability distribution of* N_0 *is given by*

$$p_0(n) = \sum_{k=H_{l,0}}^{H_{u,0}} P\left(H - k \leq \sum_{i=1}^{n-1} \tau_i^0 < H\right) P\left(\tau_n^0 = k\right), \tag{2}$$

where $p_\cdot(n) := P(N_\cdot = n)$*,* $n \in \mathcal{N}_\cdot := \{\lceil H/H_{u,\cdot}\rceil, \lceil H/H_{u,\cdot}\rceil + 1, \ldots, \lfloor H/H_{l,\cdot}\rfloor\}$*. Also,*

$$p_0(\lceil H/H_{u,0}\rceil) = \prod_{i=1}^{\lceil H/H_{u,0}\rceil} P\left(\tau_i^0 = H_{u,0}\right), \tag{3}$$

$$p_0(\lfloor H/H_{l,0}\rfloor) = \prod_{i=1}^{\lfloor H/H_{l,0}\rfloor} P\left(\tau_i^0 = H_{l,0}\right). \tag{4}$$

Proof. From (1), we require that

$$\begin{aligned} p_0(n) &= \sum_{k=H_{l,0}}^{H_{u,0}} P\left(\sum_{i=1}^{n-1} \tau_i^0 < H, \sum_{i=1}^{n} \tau_i^0 \geq H\right) \\ &= \sum_{k=H_{l,0}}^{H_{u,0}} P\left(\sum_{i=1}^{n-1} \tau_i^0 < H, \sum_{i=1}^{n-1} \tau_i^0 + k \geq H\right) P\left(\tau_n^0 = k\right) \end{aligned}$$

from which (2)–(4) follow. ■

In addition, we similarly define N_U and N_D the random number of replacements of the redesigned component with, respectively, a demonstrated substantial (up state) and minor (down state) fatigue life limitation increase during the test phase:

$$N_U = \max\left\{n\colon \sum_{i=1}^{n-1} \tau_i^U \leq H\right\}, \quad H_{l,U} \leq \tau_i^U \leq H_{u,U}, \tag{5}$$

$$N_D = \max\left\{n\colon \sum_{i=1}^{n-1} \tau_i^D \leq H\right\}, \quad H_{l,D} \leq \tau_i^D \leq H_{u,D}, \tag{6}$$

where τ_i^U and τ_i^D are the replacement durations of the i-th component at the up and down state, respectively. Under the assumption that the new component design will not vary (increase) significantly from the current one, we model τ_i^U and τ_i^D as linear transformations of τ_i^0, although this is not intended to be restrictive:

$$\tau_i^j = A^j + B^j \tau_i^0, \qquad j \in \{U, D\}, \tag{7}$$

where A^j and B^j satisfy

$$\begin{cases} A^j + B^j H_{l,0} = H_{l,j} \\ A^j + B^j H_{u,0} = H_{u,j} \end{cases}$$

with

$$H_{l,D} = H_{l,U} = H_{l,0},$$

i.e., the minimum passage of time until the first possible replacement remains unchanged, and

$$H_{u,U} > H_{u,D} > H_{u,0}$$

reflecting the improvement brought in by the redesign while allowing for different levels of such an improvement. This yields

$$A^j = \frac{H_{u,0}H_{l,j} - H_{u,j}H_{l,0}}{H_{u,0} - H_{l,0}} \text{ and } B^j = \frac{H_{u,j} - H_{l,j}}{H_{u,0} - H_{l,0}}.$$

Given (7), the probability distribution of N_U and N_D follows by analogy from (2).

As part of the project valuation approach, we consider first the standard base case value without flexibility, corresponding to the continuation of the production of the current component without any redesign. This represents the reference point for gauging the convenience of the redesign project against to. The resulting base case cost function for N_0 replacements is

$$C_B = c + C_0 (1 + N_0) N_H, \tag{8}$$

where $c \geq 0$ reflects any initial total costs, C_0 is the deterministic cost per current component per system and N_H the number of the systems. This yields an expected expenditure in the base case

$$E_B = c + C_0 (1 + E[N_0]) N_H, \tag{9}$$

where $E[N_0]$ follows from the probability distribution of N_0 specified in Proposition 1.

The manufacturing company then considers the option to switch to a redesigned component with enhanced characteristics and extended life limitation. It estimates that a three-phase model will be relevant comprising detailed design, testing and verification, and final production. This is modelled as shown on the event tree in Figure 1 and described next. An amount C_D is secured for the *detailed design* phase. With probability $q_D \geq 0$ the redesign project might be eventually decided to continue or be abandoned. At the end of this phase, the deterministic total cost C_D is incurred, in addition to potentially base costs should it be decided that the project will cease and the current component is taken to production. If it is continued, then the *prototype production and testing* phase commences. This might be particularly successful leading with probability $q_T \geq 0$ to a component with an extended fatigue life limitation $H_{u,U}$ or a less extended life limitation $H_{u,D}$. At the end of this phase, the deterministic total cost C_T associated with the test phase is incurred, in addition to the resulting cost C_1 per redesigned component per system taken to *final production.* In light of the above, the probability distribution of the cost function related to the switching option for N_U or N_D replacements (see equations 5–6) is summarized as follows:

$$C_S = \begin{cases} C_B + C_D, & \text{with probability } 1 - q_D \\ C_D + C_T + C_1 (1 + N_U) N_H, & \text{with probability } q_D q_T \\ C_D + C_T + C_1 (1 + N_D) N_H, & \text{with probability } q_D (1 - q_T) \end{cases}, \tag{10}$$

which yields expected expenditure

$$\begin{aligned} E_S &= C_D + q_D C_T \\ &\quad + N_H \left[C_0 \left(1 + E\left[N_0\right]\right)\left(1 - q_D\right) + q_D C_1 \left(1 + E\left[N_D\right]\left(1 - q_T\right) + E\left[N_U\right] q_T\right)\right]. \end{aligned} \tag{11}$$

Also, the probability distribution of the number of replacements in the switching option project, N_S, is

$$p_S(n) = p_0(n)(1 - q_D) + p_U(n) q_D q_T + p_D(n) q_D (1 - q_T),$$

where $n \in (\mathcal{N}_0 \cup \mathcal{N}_U \cup \mathcal{N}_D)$ and $\mathcal{N}_j = \{\lceil H/H_{u,j} \rceil, \lceil H/H_{u,j} \rceil + 1, \ldots, \lfloor H/H_{l,j} \rfloor\}$ for $j \in \{0, U, D\}$.

Proposition 2. *The probability that continuing the current component production costs at least as much as the switching option project is given by*

$$\begin{aligned} P(C_B \geq C_S) &= \sum_x \left[p_0\left(\frac{x - C_D - c}{N_H} - C_0\right)(1 - q_D) \right. \\ &\quad + p_U\left(\frac{x - C_D - C_T}{N_H} - C_1\right) q_D q_T \\ &\quad \left. + p_D\left(\frac{x - C_D - C_T}{N_H} - C_1\right) q_D (1 - q_T) \right] \sum_{n \geq \frac{x - c}{N_H} - C_0} p_0(n). \end{aligned}$$

where $x \in \mathcal{X}$ *and* $\mathcal{X} := \left[\left(c + C_0 \left(1 + \mathcal{N}_0\right) N_H + C_D\right) \cup_j \left(C_D + C_T + C_1 \left(1 + \mathcal{N}_j\right) N_H\right)\right]$ *for* $j \in$

$\{U, D\}$.

Proof. We have that

$$P(C_B \geq C_S) = \sum_x P(C_B \geq x) P(C_S = x),$$

where from (10),

$$\begin{aligned} P(C_S = x) &= P(C_B + C_D = x)(1 - q_D) \\ &+ P(C_D + C_T + C_1(1 + N_U) N_H = x) q_D q_T \\ &+ P(C_D + C_T + C_1(1 + N_D) N_H = x) q_D (1 - q_T) \end{aligned}$$

Then, from (8),

$$P(C_B \geq x) = P\left(N_0 \geq \frac{x - c}{N_H} - C_0\right)$$

and additionally from (10),

$$\begin{aligned} P(C_B + C_D = x) &= P\left(N_0 = \frac{x - C_D - c}{N_H} - C_0\right), \\ P(C_D + C_T + C_1(1 + N_j) N_H = x) &= P\left(N_j = \frac{x - C_D - C_T}{N_H} - C_1\right). \end{aligned}$$

■

In the following sections, we aim to exemplify the proposed project valuation approach by means of a typical case of component replacement from aeronautical engineering.

3. A case study of helicopter part redesign

It is common in the aerospace industry to sell to customers, along with the aircraft, optional services such as training for the pilots and the field operators, maintenance support, which ranges from mere supply of replacement parts to complete maintenance support comprising also mechanical maintenance technicians with 24-hour availability, and various levels of warranty. Different contractual agreements are offered to customers who are encouraged to purchase, given that the aircraft maintenance over its useful life constitutes a substantial portion of an airline's or, more generally, a flight operator's operating costs that are often comparable to the aircraft cost itself. The best-seller contract generally includes initial training for pilots and maintenance staff, replete coverage of aircraft maintenance and most of the repair costs until the aircraft reaches a certain number of operative hours.

The case that will be analyzed in this paper relates to an international aerospace company that produces and directly sells a large rotorcraft. This company adopts a commercial strategy, common in the industry, to offer maintenance programs tailored to the customers' needs. In general, maintenance programs consist of all the operations needed to maintain the helicopter fully operative, including inspections, repairs or replacement of worn components or critical components with fatigue life limitation.

A helicopter's flight control system is composed by hundreds of different components moving and rotating in order to allow the pilots to properly fly and manoeuvre the helicopter. All these components are critical parts and most of them have a limited fatigue life and their scheduled substitution is mandatory. In the case analyzed here, the maintenance program related to a particular helicopter model lasts for the period of warranty, i.e., until the aircraft reaches a maximum of $H = 3600$ flight hours. Feedback provided by the customers and the company's technicians can be very helpful. In our case study, for example, such a feedback helped identify a particular component of the system that was often found worn or damaged. Further investigation revealed that, due to poorly estimated flight loads, the component had a lower fatigue life than what predicted when the helicopter entered originally into service and, therefore, that was limited to $H_{u,0} = 300$ flight hours before being replaced. Also, the minimum duration to replacement is set equal to the number of flight hours until the first inspection is scheduled, i.e., $H_{l,0} = 5$ hours; this is nonzero to allow, for example, for potential non-conformities during inspection and installation. The replacement cost is as high as $C_0 = 3000$ USD per unit as sub-parts of this component are provided by an external supplier.

In view of the above, the manufacturer is evaluating the option to redesign the component, aiming to achieve an extended life limitation to $H_{u,U}$. To this end, they adopt the three-phase model of the previous section involving detailed design, testing and verification, and final production. Design constraints, such as the impossibility to change the component's dimensions to avoid jeopardizing the overall flight control system design, cannot be ignored and the redesign of the component can lead to a minor life limitation increase $H_{u,D} < H_{u,U}$ with $H_{u,D} > H_{u,0}$. In addition, the lapse of time to the first replacement remains unaffected by the redesign, i.e., $H_{l,D} = H_{l,U} = H_{l,0} = 5$.

The detailed design phase has an estimated cost of C_D = 125,000 USD. This phase is mainly the supplier's responsibility and the estimated chance of being approved (feasibility, acceptability of proposal, and scheduling) by the company is $q_D = 85\%$ based on prior experience with this legacy supplier. There is a remaining 15% chance that the results of the new design will be discarded and the current product will continue being released to the customers. This can be modelled as an option of continuing with or abandoning the project after the detailed design phase. If this is successful, the project can move to prototype production and testing phase during which the feasibility of the design will be verified along with its reliability. More specifically, the fatigue life limitation of the redesigned component will be assessed by means of ground testing with simulated loads and flight conditions. Based on historical information, the estimated probability that the component will be able to exhibit $H_{u,U} = 1200 > H_{u,0} = 300$ hours of service life is $q_T = 65\%$, with a remaining 35% chance of component durability of $H_{u,D} = 900 > H_{u,0} = 300$ flight hours. The estimated cost for the pre-production and testing phase is $C_T = 975{,}000$ USD with an extra cost of $C_1 = 4550$ USD per new unit when passed to the final production phase, both in addition to the non-recurring cost already allowed for in the design phase of the project. The second set of possibilities is purely driven by the performance of the redesigned component in the operations during pre-production and testing and cannot be manipulated by the management.

As said in the previous section, the event tree summarizing the entire model is shown in Figure 1. More specifically, this represents a compound option with two investment decisions: the first one relates to the design phase, whereas the second development decision is contingent on the outcome of the first phase. Two different and unrelated sources of uncertainty are present in the model: the first is economic, whereas the second is strictly technological. The different variables in the model are also summarized for convenience in Table 1, along with their initial values for the particular application and the relevant descriptions.

4. Data and model estimation

In the following, we present, for the purposes of our case study, the data on the actual performance of the current component as of the close of the year 2019. These originate from field service representatives spread on several customers' maintenance bases, then are collected by company's customer support, which is responsible for monitoring the whole fleet of $N_H = 40$ helicopters, and are finally organized and made available for internal use. In total, there are 206 components removed from helicopters already delivered to customers due to either life limitation or premature failure. These data are reported in Table 2 in terms of replacement times (measured in terms of whole flight hours from installation until removal) and the corresponding numbers of replaced components. It is worth noting that the components are visually inspected for defects, damages or failures every 5 hours and may only be removed during such inspections. Flight hours cannot exceed 300, that is, the fatigue life limitation of the current component.

Using the information in Table 2, we obtain the empirical distribution estimate of the replacement time τ^0, $\widehat{P}\left(\tau^0 = k\right)$ for all $k = H_{l,0}, 2H_{l,0}, \ldots, H_{u,0} = \alpha H_{l,0}$. This is shown in Figure 2 with observed large probability mass concentrations every 50 hours due to increased number of replacements associated with more detailed inspections performed then, leading to largest peak at 300 hours when the component reaches the upper limit of its fatigue life. The related summary statistics are presented in Table 3 with particularly reflected increased percentiles. Then, for i.i.d. $\{\tau_i^0\}_i$ and $K = H_{l,0}, \ldots, nH_{u,0}$, we define

$$Q(K,n) := P\left(\sum_{i=1}^{n} \tau_i^0 \leq K\right),$$

which, by independence of the replacement times, we compute by the following convolution

$$Q(K,n) = \sum_{k=H_{l,0}}^{H_{u,0}} Q(K-k, n-1) P\left(\tau_n^0 = k\right).$$

This can be performed easily on computing platforms such as Matlab using the built-in function `conv`. Given $\widehat{P}\left(\tau^0 = k\right)$, we also obtain from (7) the relevant probability distributions for τ^U and τ^D, as defined in (7), and the distributions of the corresponding cumulative sums of replacement times. In addition, we have confirmed our computed cumulative probabilities above against the corresponding simulated cumulative probabilities based on a random sampling procedure with replacement from our data to simulate possible values of τ^0.

Some preliminary checks are also quite informative. Figure 3 exhibits the probability distribution developed in Section 2.1 of the number of component replacements N_0 in the base case without flexibility and ongoing production of the current component as well as N_S in the component switching option model. The effect of optionality is obvious with the resulting bimodal distribution indicating, in the latter case, a smaller probability mass concentration at lower number of replacements following a successfully tested and finally produced redesigned component. A smaller probability mass concentration is observed at larger number of replacements due to potential abandonment of the redesign project with similar range to that of the current production. The flexibility introduced by the switching option is manifested in Table 4 of the relevant summary statistics with considerably decreased mean number of replacements and percentiles. The increased spread, asymmetry and tailedness originate by the option.

Having built and estimated our model for the time and number of component replacements in the current and revised production project with inherent optionalities, we next aim to investigate its cost-effectiveness for the manufacturer.

5. Analytics supporting decision making

We start our analysis by a comparison of the cost functions in Section 2.1 under the current project and the redesigned project with our proposed switching option. We use the default parameter values shown in Table 1. Figure 4 shows the probability distribution estimates for C_B (8) and C_S (10) corresponding to each case and Table 5 the relevant summary statistics. We observe a reduction in the mean cost and the percentiles, but more importantly in the standard deviation, i.e., reduction in cost uncertainty brought by the option. Not surprisingly, the shape of the probability distribution in the switching option model is rather "exotic", by nature of the project specification, and asymmetric with a slightly increased peakedness.

The impact of the redesign project depends on the number of systems – here, helicopters N_H; the level of the costs C_T of the investments during the pre-production and testing phase, which are typically high and independent from the number of the systems sold; the success probabilities q_D and q_T of the design and test phases respectively; and the difference between the current component unit cost C_0 and the redesigned component cost estimate C_1. The non-recurring costs raise the total costs of the redesign project before moving to final production, however the new component is less likely to be changed again soon; in general, the fewer the replacements, the lower the cost of the supply of the components as a response to the maintenance contracts. Moreover, the effect of the non-recurring costs on the total expenditure reduces when they are allotted across more systems. In fact, the latter turns out to be a primary factor driving the cost discrepancy between the base case project and the project with incorporated switching option.

A comprehensive study of the potential driving factors is the object of the following sections. This can be used to assess the importance and level of influence of the different variables as well as the importance of using accurate estimates for the input parameters aiming to limit the exposure to misspecification risk. The cost functions C_B and C_S are linked with the expected expenditures E_B and E_S given by (9) and (11). The probability of a more cost-effective redesign project $P(C_B \geq C_S)$ is computed analytically as shown in Proposition 2. For the purposes of our exercise, we set ranges of variation for the various underlying variables. For example, the range for N_H is consistent with expected fleet size increments in the near future and in the medium term before stabilizing due to the long life cycle of the helicopter. Fixed costs, like the aggregate C_T and C_1 per redesigned component, are educated estimates based on the historical costs for the improvements undertaken during the redesign. The probabilities q_D and q_T are based on historical data and prior knowledge from previous related projects.

5.1. Number of systems and design phase joint effects

Figures 5–6 are devoted to a study of the expected expenditure as a function of N_H and q_D. More specifically, the grey surface in Figure 5 indicates a linearly increasing E_B with N_H and is independent of q_D. On other other hand, E_S, given by the blue surface, is bilinear in N_H and q_D. This as well as the resulting expected cost E_S dropping below the base case cost E_B are indeed anticipated for a higher chance of continuation of the redesign project applicable to a larger fleet. This is more closely seen in Figure 6 which exhibits the contour levels of the difference of the expected costs of the two strategies. The contour curves, represented by hyperbolas, associated with negative (positive) values indicate that the redesign strategy is characterized by a lower (higher) expected cost. In particular, the contour curve of level 0 represents the combinations of helicopters sold and levels of carrying-on probability with the new strategy such that the manufacturer breaks even. On the same plot, the red spot corresponds to the default values $(N_H, q_D) = (40, 85\%)$. Moreover, for unchanged $N_H = 40$, the redesign project generates a lower expected cost even with a q_D that is as low as 67%. For a small N_H, the saving brought in by the enhancedly performing redesigned component is unable to outweigh the fixed costs. Indeed, Figure 5 shows that, for relatively small N_H, E_S as a function of q_D is downward-sloping, albeit only slightly, and is always above E_B. Instead, the relationship between E_S and q_D is reversed becoming upward-sloping for sufficiently large N_H. The contour plot stresses that even for an absurd probability of 10% of a successful design phase, a fleet size larger than 80 suffices for a more cost-saving redesign project.

Similar conclusions emerge from Figure 7 which exhibits the probability of a cost-effective redesign strategy, $P(C_B \geq C_S)$, as a function of N_H and q_D; in addition, Figure 8 shows the contour curves of the probability surface. As before, the likelihood of a more cost-effective redesign project increases with N_H and q_D. We focus the spotlight on three different levels of $P(C_B \geq C_S)$: 10%, 50% and 90%, including the default combination $(N_H, q_D) = (40, 85\%)$ indicated by the red mark. For $N_H = 40$ and a very unusually low $q_D = 30\%$, the redesign cost has a 10% chance to be lower than the base cost. With q_D rising to 80%, that is, closer to its market estimated value, the probability of a lower cost increases to 50%. For the default value of $q_D = 85\%$, the probability of having a lower cost is as high as 90% for around 50 helicopters sold, which is welcome news for the efficiency of our proposed model framework. The contour plot confirms the relative importance of having a large fleet size. If q_D is as small as 10%, the redesign project becomes cost-saving with an above 50% probability when N_H exceeds 70. With N_H close to 100, this probability rises to 90%. This is also seen in Figure 7 where, for relatively small (large) $N_H < 30$ ($N_H > 75$), the probability of having a lower cost is near zero (one).

5.2. Number of systems and test phase joint effects

Once the project moves to the test phase, it is sensible to study also the effect of the probability q_T of a successful, significant increase of the component's life limit. Qualitatively, we observe a similar pattern as with q_D in the design phase. Figures 9–10 examine the expected cost and the probability of achieving a lower cost as a function of N_H and q_T. The expected cost of the current base project is unvarying with q_T, whereas incorporating the switching option results in a bilinear expected cost function of both variables (with contour levels for the expected cost differences in the form of a hyperbola, omitted from the paper in the interest of space). For the default values $(N_H, q_T) = (40, 65\%)$, the redesign project yields a slightly lower expected cost and the probability that the cost is actually lower than that of the current production is just above 50%. For $N_H = 60$ and an extremely unambitious test phase with $q_T = 10\%$, noting that the default value $q_T = 65\%$ is much higher as the project does not rely on new technologies whose potential or drawbacks are yet to be discovered, the proposed model is still able to ensure that the redesign strategy has a lower cost with 90% chance. These numbers confirm the predominant effect of a large fleet almost despite the q_T level. This is also shown in Figure 11 where varying N_H affects the rate of increase of the cost-effectiveness likelihood of the proposed strategy: extremely small or large N_H has a flattening effect on this, whereas gradually increasing N_H in between yields an upward-sloping trend that is steepest around $N_H = 40$ before it starts flattening again at 90% chance. This is due to the accumulating costs (C_0 and C_1 per component) with increasing N_H.

5.3. *Number of systems and costing joint effects*

Next, we study the combined effect of N_H and the fixed cost C_T incurred in the test phase. As shown in Figure 12, the latter affects only the expected cost of the redesign project in a linear fashion. (Similar observations are made for different fixed C_D levels in the design phase.) Quite predictably, increasing C_T can have a detrimental effect on the project profitability. However, for sufficiently large N_H, the total cost remains below that of the base project for reasonably varied C_T: when $N_H = 40$, the redesign project becomes profitable when C_T is lower than 1.1 million USD, which includes the default cost value of 975,000 USD. For a larger N_H, the fixed costs are not affected and, therefore, the proposed project remains financially sustainable even for higher C_T levels: for example, for $N_H = 50$, the project profitability is able to withstand a C_T increase to 1.3 million USD. These arguments are reflected in Figure 13, where the negative impact of C_T on $P(C_B \geq C_S)$ is made obvious, but more importantly it is shown how this probability increases with N_H and its decay rate decreases (changing curvature) with it. In fact, controlling the cost of this phase is crucial for the profitability of the project, as its effect on the total costs is larger than that of the other variables seen.

5.4. *Number of systems and joint phase effects*

Lastly, we study the joint impact of varying probabilities q_D and q_T of, respectively, passing the design phase and successfully testing the new component. The base project cost is not affected by these changes: the grey surface in Figure 14 is indeed flat. For the reference values $N_H = 40$, $q_D = 85\%$ and $q_T = 65\%$, the redesign project is characterized by a lower expected cost, whereas it breaks even at $q_T = 50\%$. As already mentioned, the default value $q_T = 65\%$ is sensibly much higher as the new technologies used have known potentials. Instead, a low q_D is associated with more uncertainties in the design phase, obscuring the overall cost reduction effect.

In Figure 13, we additionally introduce the effect of varying N_H. We see that increasing N_H, with q_T and q_D held fixed at their maximum level of 1, results in the steepest and highest cost-effectiveness likelihood of the redesign strategy. Quite naturally, intermediate q_T and q_D values have a clockwise swivelling effect; this becomes particularly interesting for small N_H as the probability $P(C_B \geq C_S)$ in that region is larger than for $q_T = q_D = 1$ due to lower accumulated costs (C_0 and C_1 per component). Even more interestingly, $P(C_B \geq C_S)$ becomes larger and flatter in the unlikely extreme case of $q_T = q_D = 0$ for even moderate N_H values.

5.5. Stochastic dominance in the component replacement problem

We complete our analysis by an application of stochastic dominance rules in our manufacturer's component replacement problem. We are interested in seeing whether an unambiguous decision between the two alternatives can be made, independently of the manufacturer's utility function. Given two uncertain positions with cumulative distribution functions F and G, the stochastic dominance theory provides conditions for preference of F over G for any utility function u in a function set $\mathcal{U}_i$, i.e.,

$$E_F\left[u\left(X\right)\right] \geq E_G\left[u\left(X\right)\right], \quad \forall u \in \mathcal{U}_i \text{ and } X \in \mathcal{X},$$

where $\mathcal{X}$ is defined in Proposition 2. Depending on the function set, we can have various stochastic dominance orders; we focus on the first three rules ($i = 1, 2, 3$) with most economic meaning. $\mathcal{U}_1$ includes all u with $u' \geq 0$, i.e., all increasing utility functions and we say that F dominates G in a first-order stochastic dominance (FSD) sense. Hadar and Russell (1969) and Rothschild and Stiglitz (1970) introduced the less restrictive second-order stochastic dominance (SSD) by considering the set $\mathcal{U}_2$ of increasing and concave utility functions, i.e., this includes all u with $u' \geq 0$ and $u'' \leq 0$. Finally, Whitmore (1970) introduced the third-degree stochastic dominance (TSD) for the class of utility functions $\mathcal{U}_3$, including all u with $u' \geq 0$, $u'' \leq 0$ and $u''' \geq 0$, such that the risk premium associated with an uncertain prospect becomes smaller for larger wealth. (See also Levy, 1992.) The stochastic dominance rules and the associated utility function classes are summarized as follows:

$$\begin{aligned}
&\text{FSD:} \quad && G(x) \geq F(x), \ \forall x \in \mathcal{X}, \\
&\text{SSD:} \quad && \int_{\mathcal{X}_{\min}}^{x} G(s)ds \geq \int_{\mathcal{X}_{\min}}^{x} F(s)ds, \ \forall x \in \mathcal{X}, \\
&\text{TSD:} \quad && \int_{\mathcal{X}_{\min}}^{x} \int_{\mathcal{X}_{\min}}^{y} G(s)dsdy \geq \int_{\mathcal{X}_{\min}}^{x} \int_{\mathcal{X}_{\min}}^{y} F(s)dsdy, \ \forall x, y \in \mathcal{X}, \text{ and } E_F\left[X\right] \geq E_G\left[X\right].
\end{aligned}$$

(Note that at least one strict inequality must hold in all cases.)

The previous stochastic dominance criteria allow us to rank the two risky prospects. In particular, we determine the fleet size threshold levels such that the switching strategy dominates the base strategy, or vice versa, according to each of the three criteria. Figure 16 shows that if the fleet size N_H is equal to 30, the base project dominates the switching strategy by all FSD, SSD and TSD, and vice versa if $N_H = 50$. For our reference value $N_H = 40$, no conclusive decision can be made as the (integrated) cumulative distribution functions cross each other, hence there is no clear-cut dominant strategy. However, as mentioned at the beginning of Section 5, considerable fleet size increments expected in the short term are very encouraging for a manufacturer that considers changing the component production plan in the near future. More specifically, Table 6 reports that for N_H larger than 48, the switching strategy dominates the current production position by FSD (and, therefore, SSD and TSD). For $N_H \geq 45$, the switching option strategy dominates by SSD (and, therefore, TSD); for $N_H \geq 43$, it dominates by TSD. The base project becomes only dominant over the proposed redesign project by FSD in the rather implausible case of a fleet size of 33.

6. Conclusions

In this paper, we devise a model that incorporates a switching option in the evolution of a redesigned replacement component project accounting for large costs and uncertainties in the decisions to be made at the different sequential stages. The approach herein provides a structured methodology including the model framework, analytical model estimation using real data, project evaluation and cost-effectiveness analysis.

The paper focuses on a case study application of the proposed framework in aeronautics. It is shown that the selection between project abandonment or continuation with redesigned component replacement represents a valuable option which, given the various uncertainties, manifestly increases the likelihood of cost-effectiveness over an unchanged production position. We study the effect of key variables in the project evolution, including the number of systems sold, fixed costs involved and probabilities of successfully passing the different phases. It is found that the number of systems sold is the key driver of the cost reduction brought in by our redesign project. Consistently with prevailing and imminent market conditions, this yields cost-effectiveness with at least 90% chance and stochastic dominance of our proposed redesign project over the current risky production by first order. Finally, as part of our sensitivity analysis, this has also been able to withstand extremely stressed costs and low phase success probabilities, having been shown cost-effective with more than 50% chance.

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Notation	Description	Default value
c	Initial total cost (\$)	0
C_D	Deterministic total cost (\$) of preliminary design phase	125,000
C_T	Deterministic total cost (\$) of pre-production and test phase	975,000
C_0	Unit cost (\$) of current component	3000
C_1	Unit cost (\$) of redesigned component	4550
N_0	Replacements of current component	Random
N_U	Replacements of redesigned component (substantially increased fatigue life)	Random
N_D	Replacements of redesigned component with (minor fatigue life increase)	Random
N_H	Number of systems sold	40
q_D	Probability of project continuation following detailed design	85%
q_T	Probability of success of test phase	65%
τ^0	Current component replacement time	Random
τ^U	Redesigned component replacement time (considerable fatigue life increase)	Random
τ^D	Redesigned component replacement time (minor fatigue life increase)	Random
$H_{l,\cdot}$	Flight hours until first inspection	5
$H_{u,0}$	Fatigue life limitation (hours) of current component	300
$H_{u,U}$	Fatigue life limitation (hours) of redesigned component (considerable fatigue life increase)	1200
$H_{u,D}$	Fatigue life limitation (hours) of redesigned component (minor fatigue life increase)	900

Table 1: Model variables and parameters.

Replacement time (flight hours)	Number of components replaced	Replacement time (flight hours)	Number of components replaced
5	1	195	6
30	1	200	16
45	1	205	7
50	6	210	6
55	3	225	3
85	2	250	3
95	11	255	6
100	18	260	6
105	7	265	8
125	2	270	6
145	3	275	3
150	12	290	6
155	3	295	8
180	3	300	48
190	1	**Total**	206

Table 2: Replacement times and corresponding numbers of components replaced based on data provided for the entire helicopters fleet. Source: Company's customer support and feedback from technicians performing maintenance as of close of year 2019.

Replacement time statistics	
Mean	206.89
Standard deviation	84.15
10th percentile	95
25th percentile	125
Median	210
75th percentile	295
90th percentile	300

Table 3: Summary statistics of component replacement time (in hours) τ^0.

Number of replacements statistics	Base case N_0	Redesign project N_S
Mean	16.97	6.31
Standard deviation	1.74	4.66
Skewness	0.37	1.83
Kurtosis	3.16	4.88
Median	17	5
75th percentile	18	6
90th percentile	19	16
99th percentile	21	20

Table 4: Summary statistics of number of replacements distribution: base case (N_0) versus redesign project (switching option) (N_S).

Project cost statistics	Base case C_B	Redesign project C_S
Mean	2,156,907	2,125,024
Standard deviation	208,644	164,336
Skewness	0.373	0.677
Kurtosis	3.162	3.472
Median	2,160,000	2,105,395
75th percentile	2,280,000	2,242,095
90th percentile	2,400,000	2,332,240
99th percentile	2,640,000	2,587,495

Table 5: Summary statistics of project cost (USD) distribution: base case (C_B) versus redesign project (switching option) (C_S).

Criteria	Base $\succ_{SD}$ Switching	Switching $\succ_{SD}$ Base
FSD	33	48
SSD	38	45
TSD	39	43

Table 6: Critical fleet size levels N_H of stochastic dominance of switching option strategy over the base project (Switching $\succ_{SD}$ Base), and vice versa, by first order (FSD), second order (SSD) and third order (TSD). Second (third) column shows the maximum fleet size such that the base (switching option) project is preferred by SD.

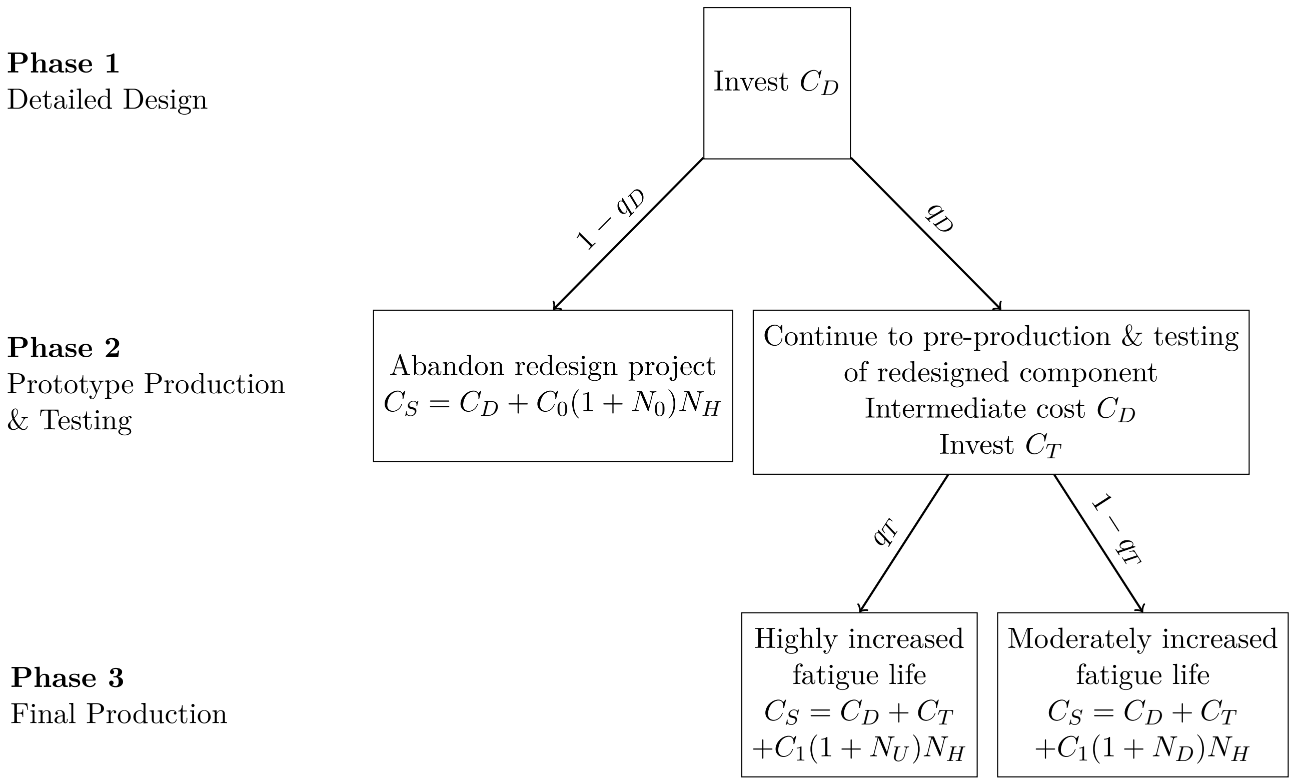

Figure 1: Event tree.

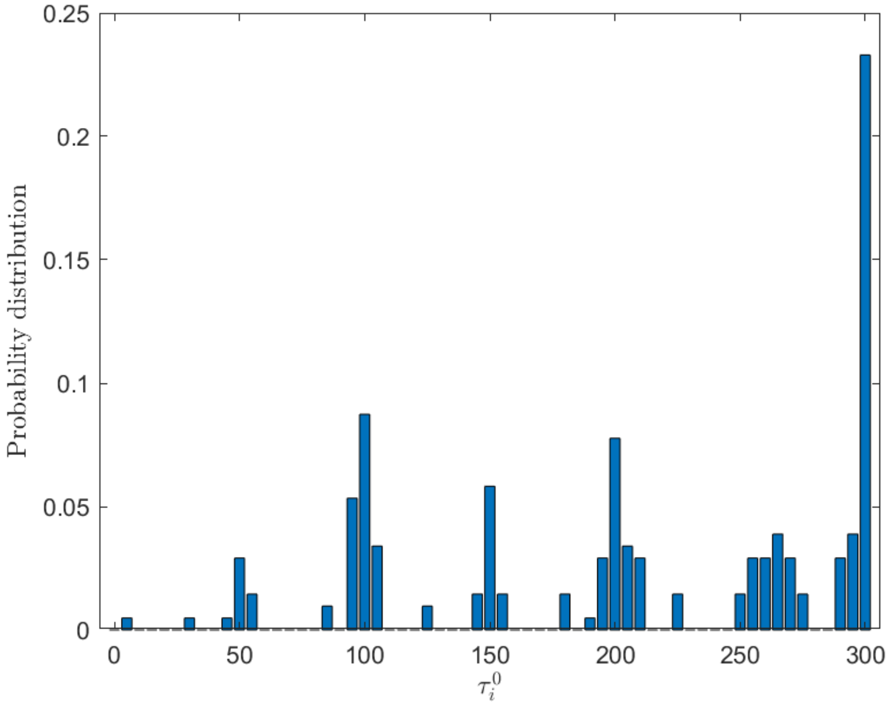

Figure 2: Probability distribution of replacement time.

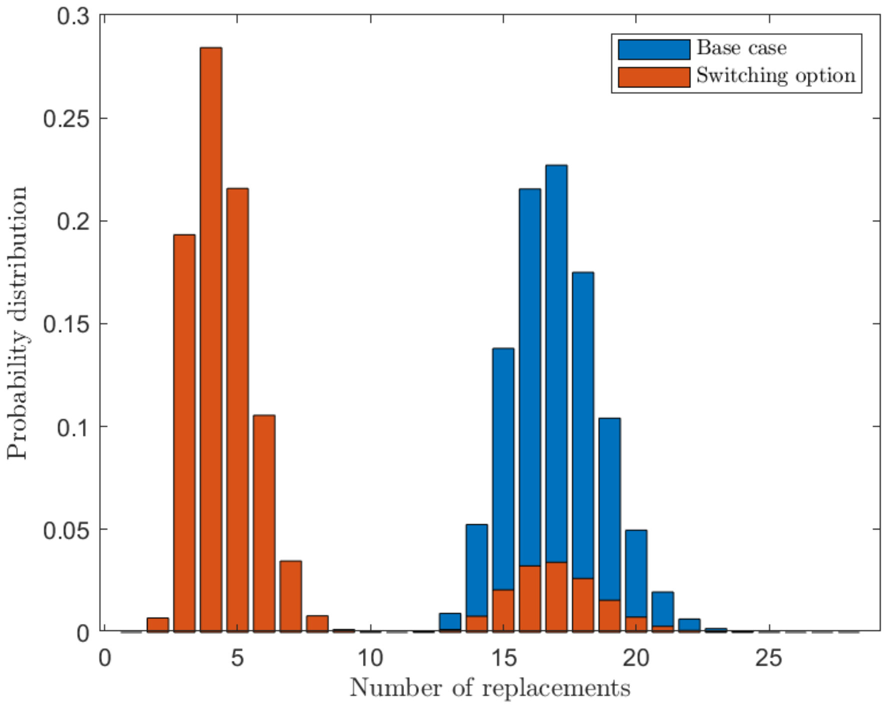

Figure 3: Probability distributions of N_0 and N_S: base case and redesign project with switching option.

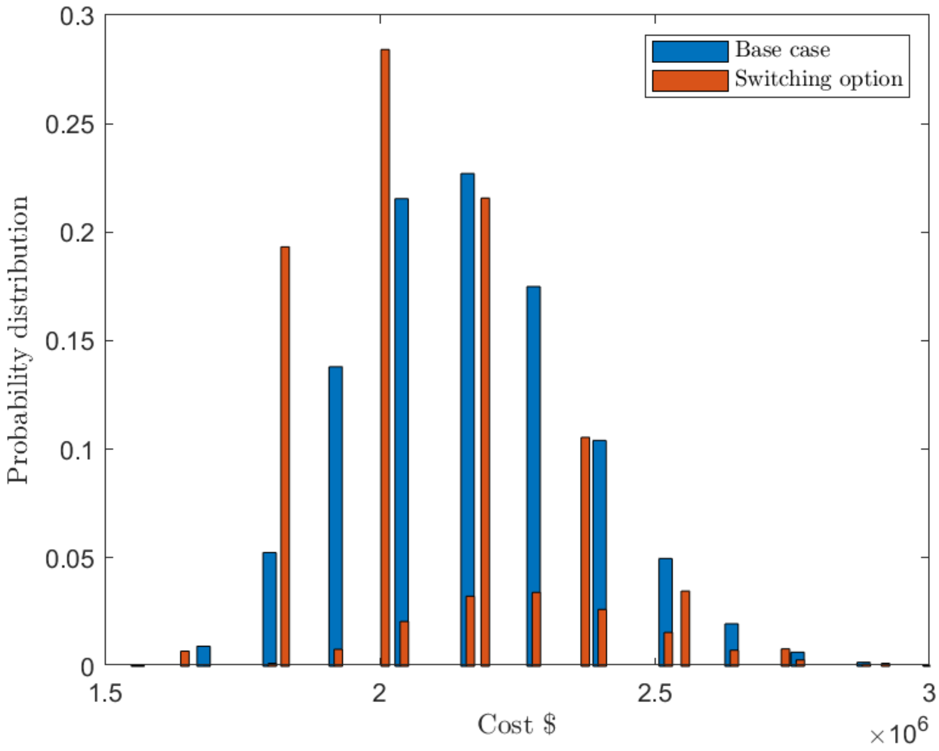

Figure 4: Probability distributions of cost functions C_B and C_S: base case and redesign project with switching option.

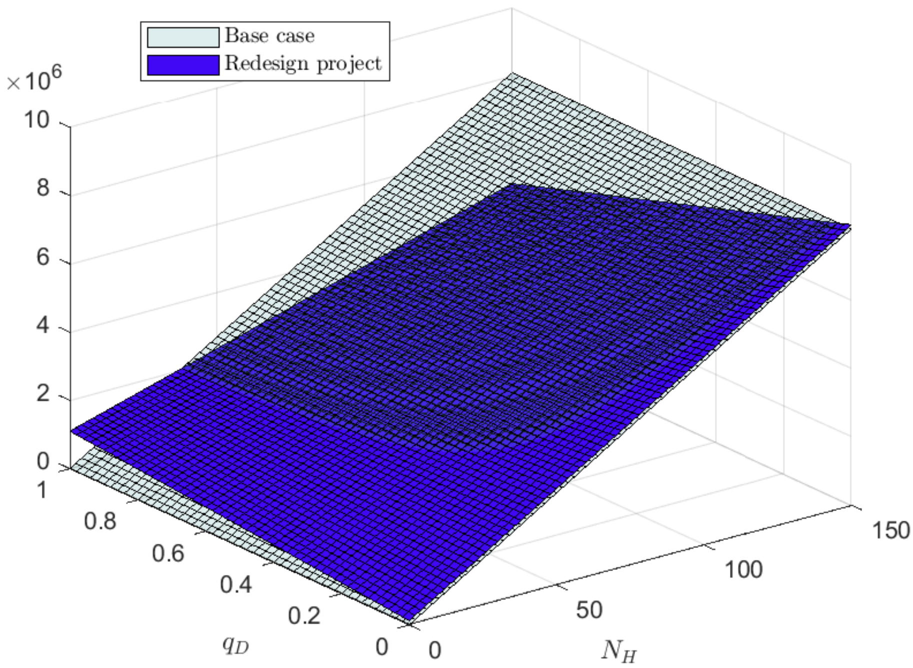

Figure 5: Joint effect of probability q_D of project continuation and fleet size N_H on expected expenditures E_B and E_S: base case and redesign project with switching option.

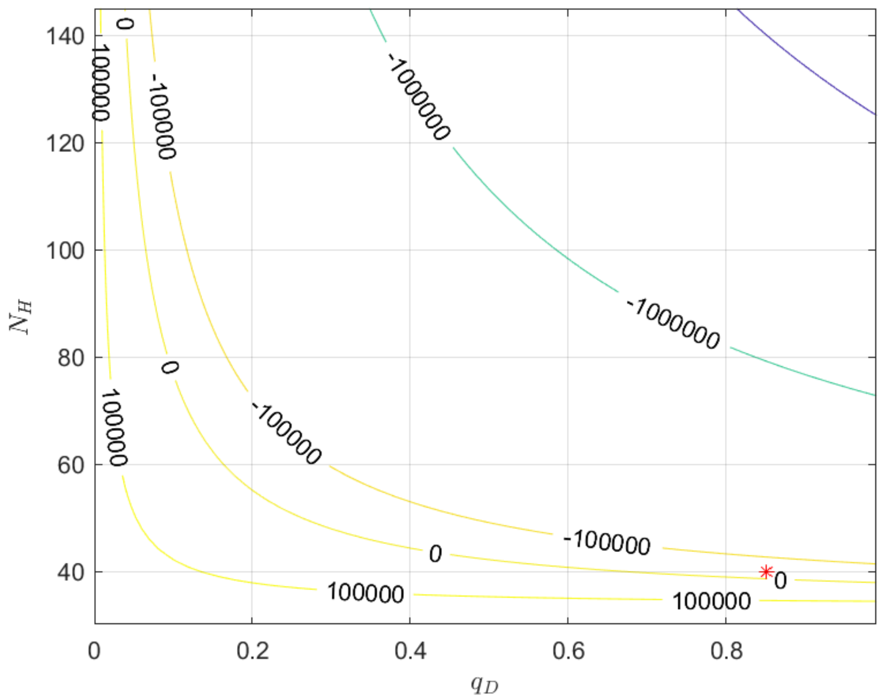

Figure 6: Contour levels of differences of expected expenditures ($E_S - E_B$) as function of probability q_D of project continuation and fleet size N_H.

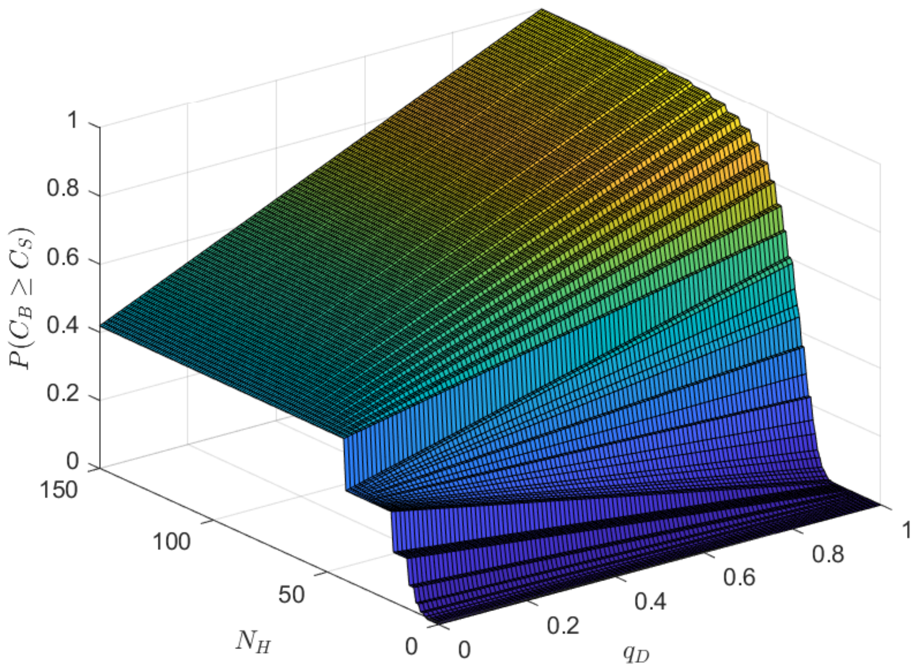

Figure 7: Probability of costlier current component production than redesign project with switching option with varying probability q_D of project continuation and fleet size N_H.

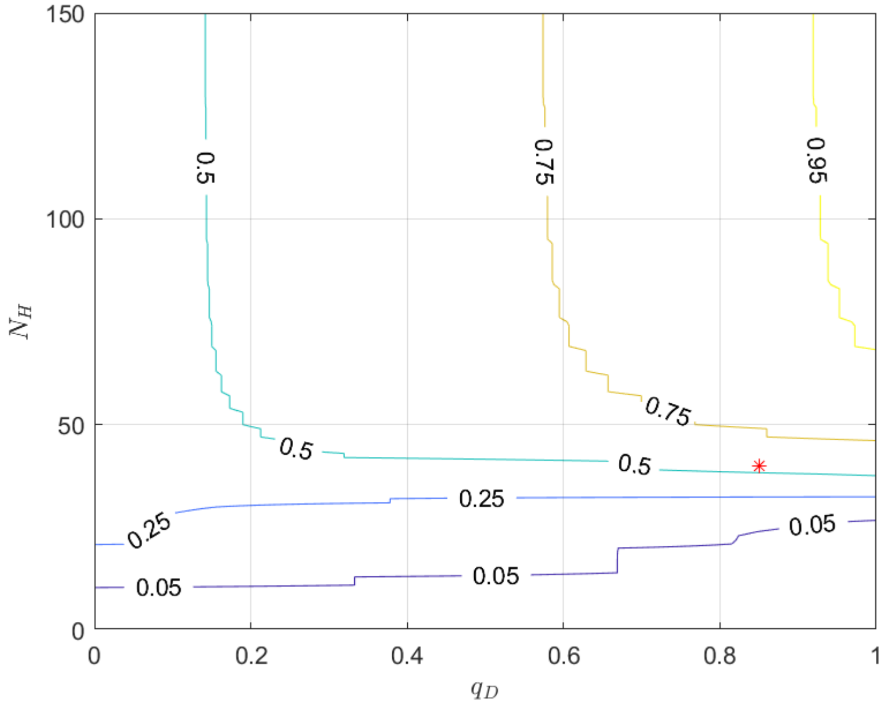

Figure 8: Contour levels of probability of costlier current component production with varying probability q_D of project continuation and fleet size N_H.

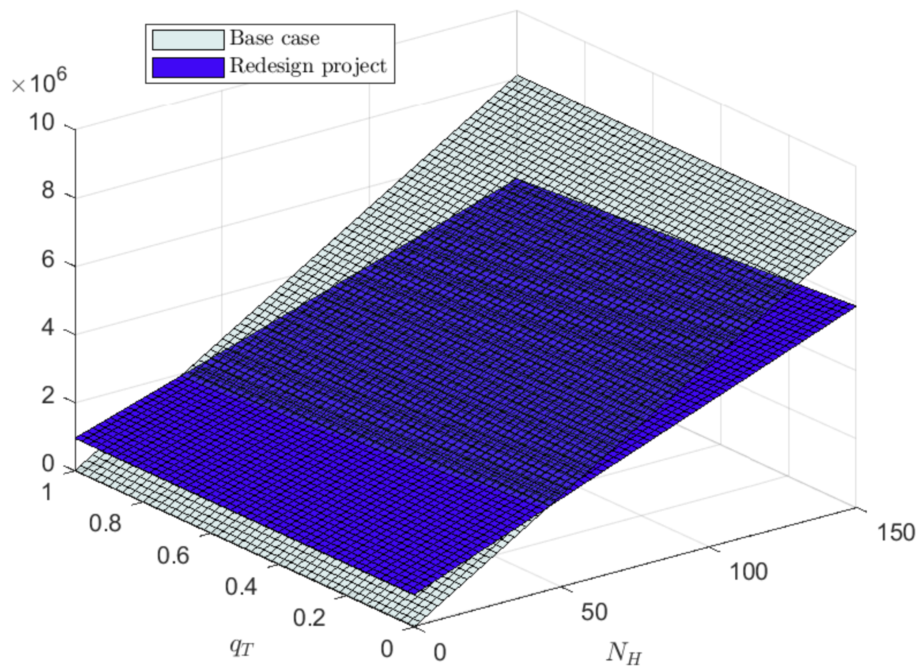

Figure 9: Joint effect of probability q_T of successful testing and fleet size N_H on expected expenditures E_B and E_S.

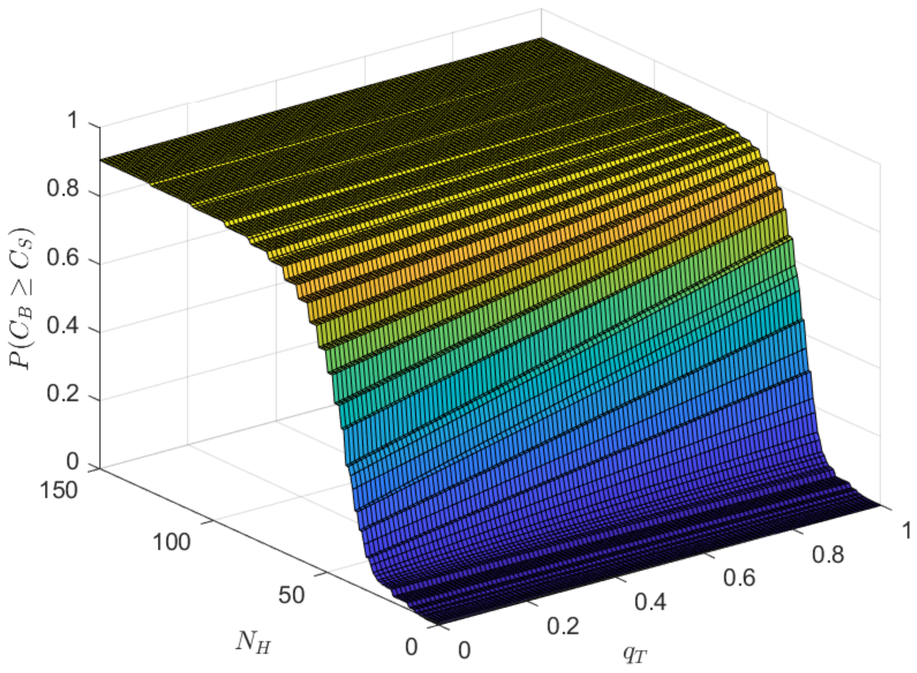

Figure 10: Probability of costlier current component production than redesign project with switching option with varying probability q_T of successful testing and fleet size N_H.

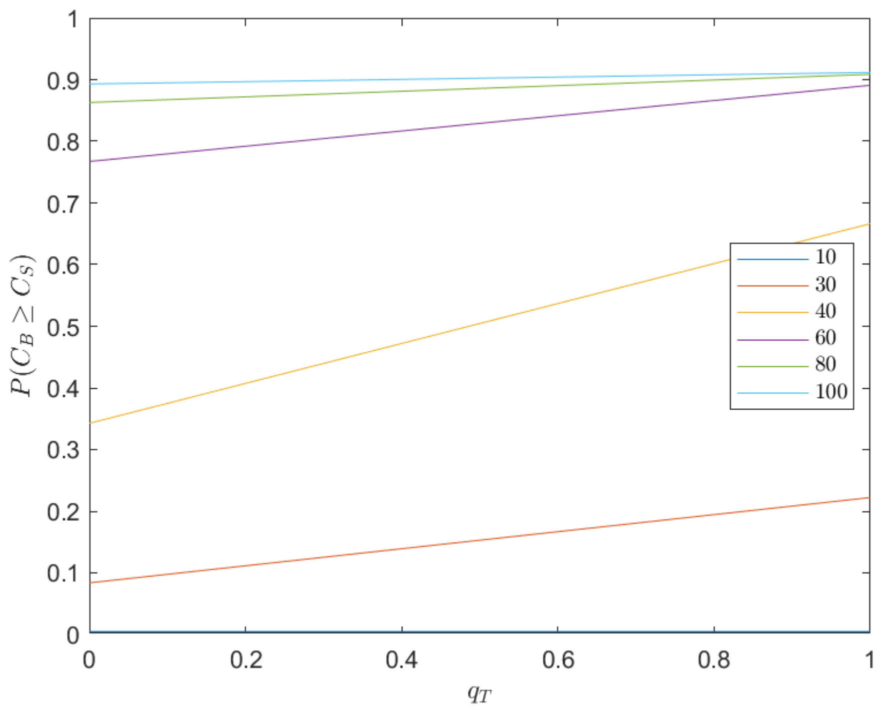

Figure 11: Probability of costlier current component production as function of probability q_T of successful testing for varying fleet size N_H.

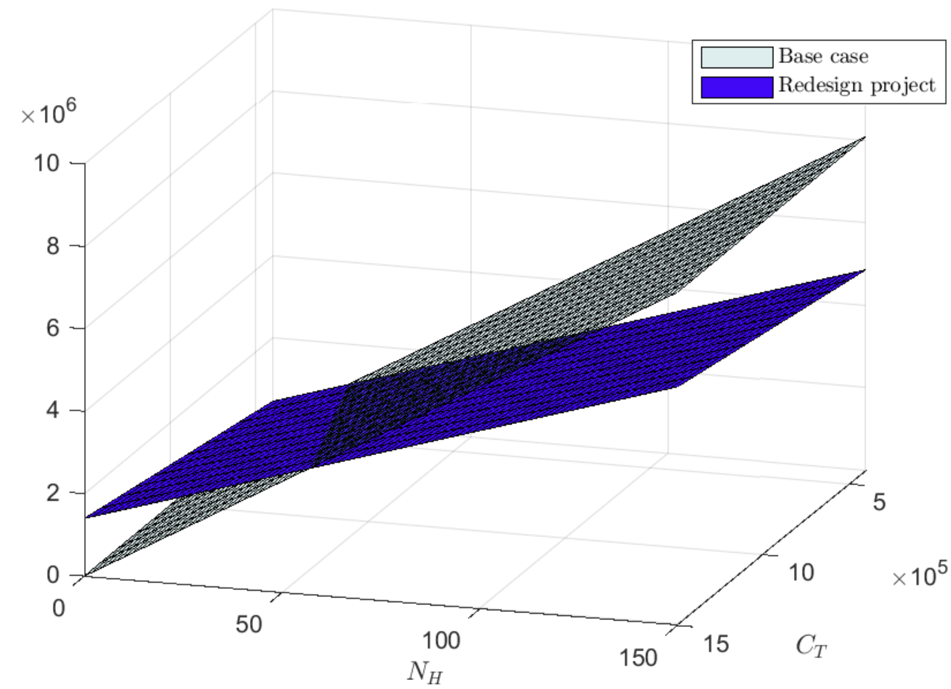

Figure 12: Joint effect of pre-production and testing cost C_T and fleet size N_H on expected expenditures E_B and E_S.

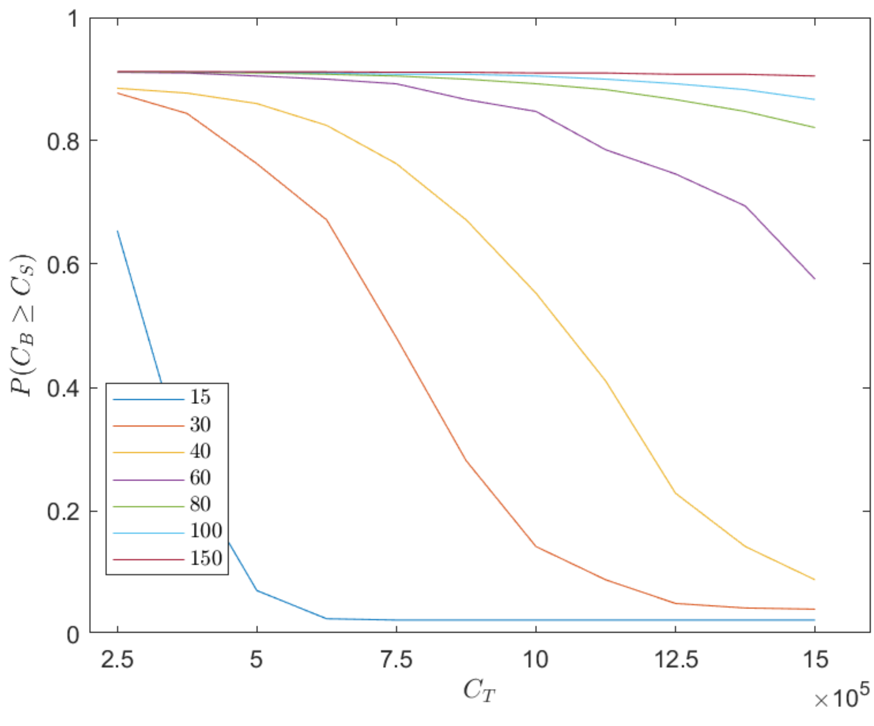

Figure 13: Probability of costlier current component production as function of pre-production and testing cost C_T for varying fleet size N_H.

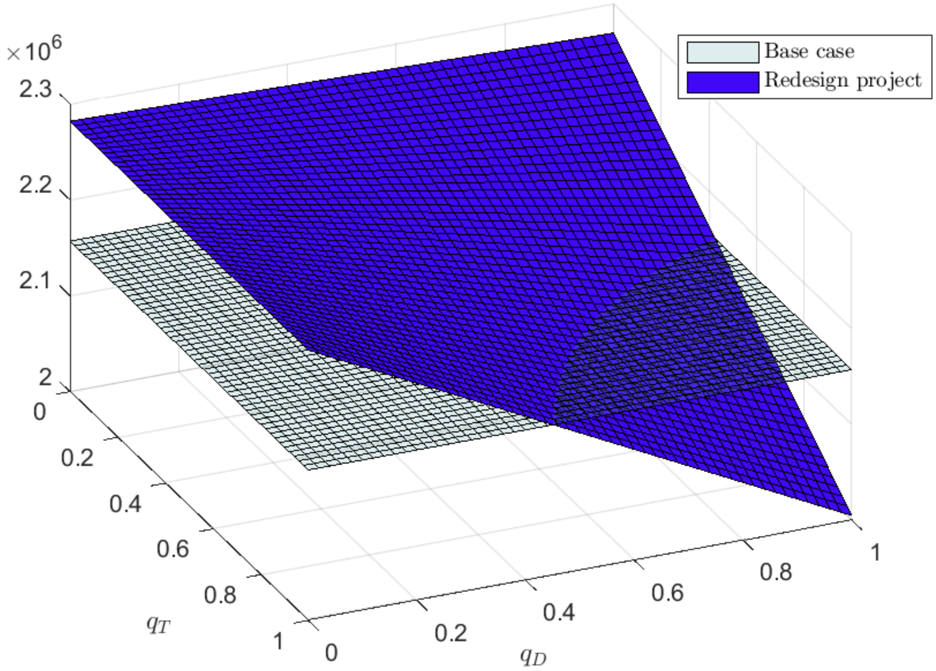

Figure 14: Joint effect of probability q_D of project continuation and probability q_T of successful testing on expected expenditures E_B and E_S.

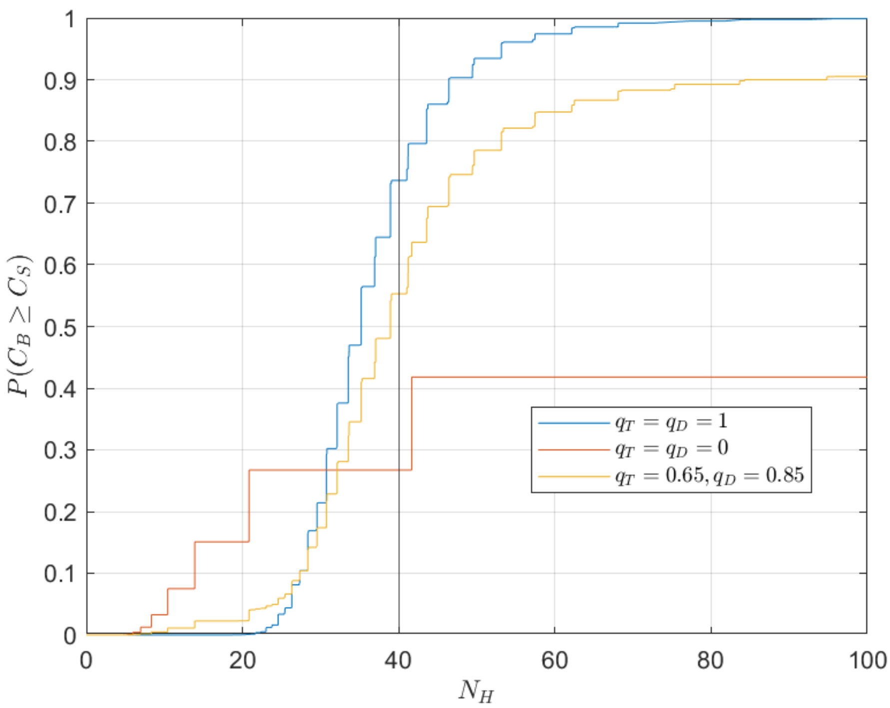

Figure 15: Probability of costlier current component production as function of fleet size N_H for varying probability q_D of project continuation and probability q_T of successful testing.

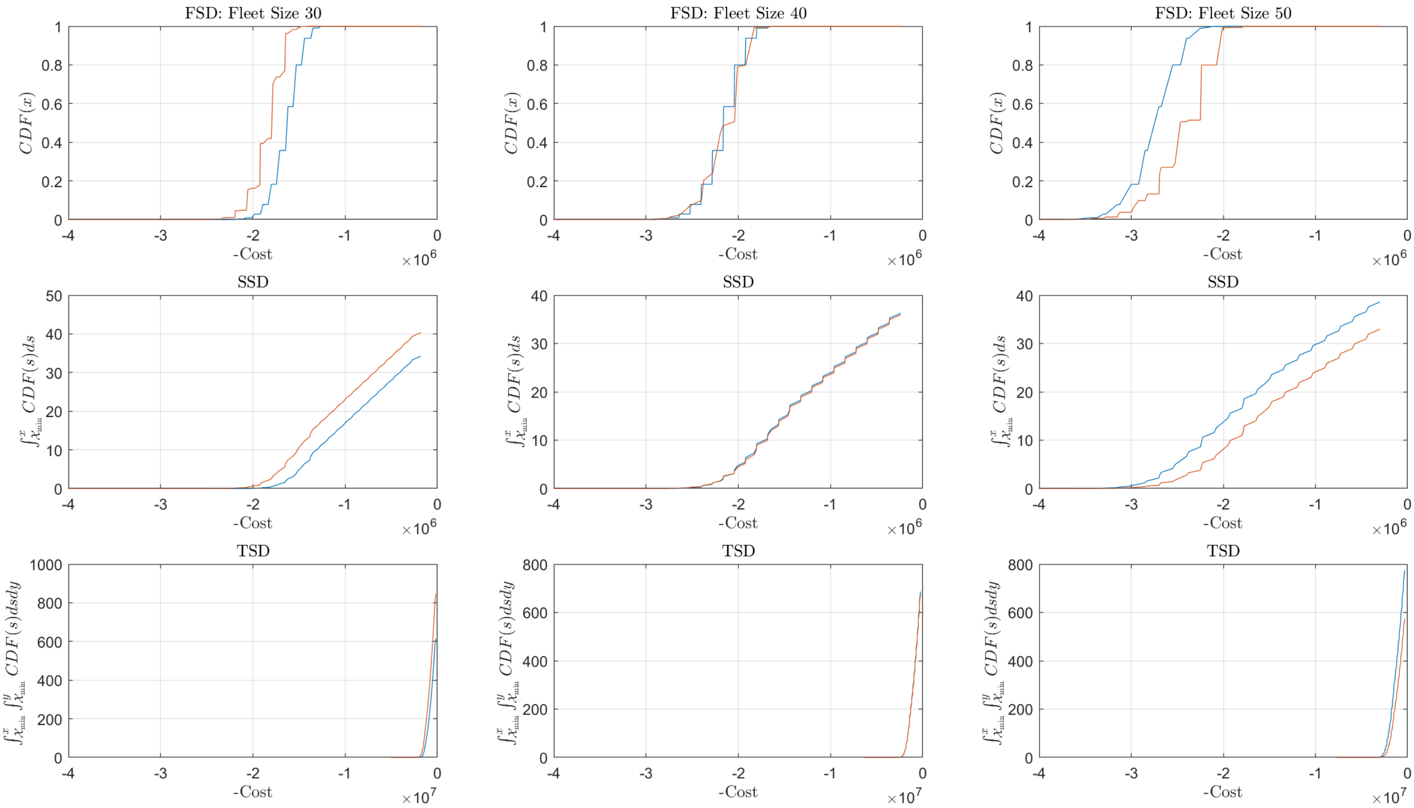

Figure 16: Analysis of stochastic dominance in the component replacement problem for varying fleet size N_H and order of stochastic dominance. A comparison between the base project (blue) and the switching option strategy (orange).