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Statistical Simulation of Life Cycle Cost

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Abstract: This paper contributes to literature aiming to improve corporate decision-making policies in times of depressed margins and increased business uncertainty. Starting from a case study based on actual servicing systems, it develops and applies a value-based decision-making model using a combination of life cycle costing and statistical simulation. It is shown that this approach generates meaningful results wherever there are alternative solutions available for component parts of servicing units, differing in a range of functional characteristics and involving risk. In contrast to conventional capital budgeting, such a model provides full assessment of contingent or intangible costs, such as the impacts of device reliability. Simulation results and their reliability can be analyzed using standard statistical methods. Sensitivity analyses are vital for the determination of relevant risk factors.

Keywords: capital budgeting; life cycle cost; statistical simulation

JEL Classification: M21; C44

1. Introduction

Several industries, including e.g. automotive, logistics and retail, are facing intensive competitive and regulatory pressures, squeeze on margins and business model disruption (KPMG 2019). This makes it more important than ever to pursue rigorous policies and use decision-making techniques with a clear focus on value, and considering exogenous, as well as endogenous uncertainty (Hellemo et al. 2018, Maier et al. 2019). In contrast to conventional capital budgeting, focusing on nonrecurring and time-constrained investments and neglecting systemic feedbacks, various factors of risk can be incorporated into decision-making using statistical simulation combined with life cycle costing.

These two methods are otherwise quite commonly used separately in different contexts, as shown by Dhillon (2010) and Mordechai (2011), respectively. For example, Fulton (2018) compared total life costs of electric and hybrid drive vehicles, Favi et al. (2018) analyzed the design process in shipbuilding and El-Akruti at al. (2016) determined the optimal repair and replacement policies for an electric arc furnace used in the steel industry using life cycle costing, while Vlachý (2018) analyzed the choice in product distribution and Dui et al. (2018) optimized the energy storage capacity for wind farms using statistical simulation.

Their merging allows the temporal and functional normalization of mutually exclusive decisions (through life cycle costing) in the context of dynamic systems (through statistical simulation). Possible applications may then range from assessing decisions in potentially high-growth innovation industries to those relating to choices in product distribution, as shown by Vlachý (2017; 2018). Relevant in the present context is a defining feature of life cycle cost analysis, which may use relative - rather than absolute - valuation when selecting one of several solutions to a particular engineering design, resulting in considerably reduced input data requirements (Norris 2001; Dhillon 2010). This, in turn, facilitates the creation of a relatively simple and robust simulation model (Mun 2015). Furthermore, as explained by Norris (2001) and Kong and Frangopol (2003), and shown by Table 1, life cycle cost analysis may extend the scope of costs above those of Type I (direct) and Type II (indirect), used in conventional costing, to include Type III (contingent) and Type IV (intangible), which are typically relevant in systems featuring operational or strategic risks that can be best assessed using simulation (Vlachý 2009). It may be noted that somewhat less flexible alternatives - that would not be suitable for such a methodological integration - include closed/form analytical solutions and decision trees (Broadie and Detemple 2004).

This paper solves a problem, initially based in logistics, but relevant also for other types of servicing systems. These typically contain various critical components that need to be periodically maintained, renewed or replaced to achieve a particular service standard at optimal cost, as demonstrated in the context of medical devices by Sinclair (2010) and, in more general terms, by Volkman (1997). When taken as individual capital budget decisions, they are thus relatively small, but their overall impact on the system is significant (Chang 2010). A model will be developed that can be further generalized and used for more broadly conceived problem classes. Finally, for the current problem, parametric sensitivities will be tested, addressing the errors-in-variables factor, whose relevance in economic models is discussed in detail by Chen et al. (2015).

Summarily, the study thus aims to improve corporate decision-making, in particular involving situations featuring increased business uncertainty and depressed business margins.

Table 1. Description of cost types. (source: adapted from Norris 2001 and Frangopol 2003)

Cost type	Description
Type I (Direct)	Direct costs of capital investment, labor, raw material, waste disposal; may include both recurring and non-recurring costs.
Type II (Indirect)	Indirect costs not allocated to the product or process; may include both recurring and non-recurring costs.
Type III (Contingent)	Contingent costs such as fines and penalties, personal injury or property damage liabilities, production or service disruption, competitive response, etc.
Type IV (Intangible)	Difficult to measure costs, including customer acceptance, customer loyalty, worker morale, community relations, corporate image.

2. Methodology

The case that will be solved is defined as follows: An essential component in a handling mechanism can be designed using two alternative technologies (A or B). Their characteristics differ in four life cycle phases, production of the component, its installation, its use in operation, and its disposal including dismounting. Generally speaking, technology A is more sophisticated and expensive, which involves higher costs of production, higher costs of installation, and the need to install an additional control component. It also has a shorter working life and worse reliability (i.e. higher probability of premature breakdown, which is negligible for a Type B component). On the other hand, due to improved controls and enhanced automatization, technology A decreases power consumption and reduces personnel costs.

Several distinct operating assumptions are involved: Type A components can be refurbished, up to two times each, and there are defined costs (including opportunity costs) to each unscheduled service disruption. Each handling mechanism (which is otherwise the same regardless of the technology used in its component that is being evaluated) has a defined annual operating time and handling capacity, as well as a life expectation in terms of handled units. To avoid clearly purposeless component replacements just before the handling mechanism is due for retirement, they will be retained when the handling mechanism's life exceeds a pre-set number of handled units (this parameter is designated ξ).

A summary of the model inputs, including the particular values used in the case, is provided in Table 2.

Table 2. Model inputs summary.

Parameter [unit]	Description	Value (Type A)	Value (Type B)
P [€]	Component production cost	4,800	4,000
I [€]	Component installation cost	500	400
C [€]	Control device cost	1,500 (only installed once / part of mechanism)	N/A
τ [units]	Replacement time	175,000	200,000
D [€]	Disposal cost	500	500
R [€]	Refurbishment cost	1,800	N/A
m	Maximum number of component refurbishments	2	0
ξ [units]	Maximum framework life for component replacement	900,000	900,000
X [€]	Service disruption cost	900	N/A
λ [units]	Mean life expectation of component	250,000	N/A
ρ [units]	Actual component life	stochastic (exponential distribution with parameter λ)	200,000

When using life cycle costing, it is vital to determine a suitable functional unit. In the present case, the operation cycle is best defined as a number of processed units, which is a common quotient for the handling mechanism life, as well as for the life determinants its component, and becomes a common measure of service time. Accordingly, 100,000 processed units will be used as the model's functional unit. This also determines the discount rate; given the 8 % annual rate and the annual handling capacity of 160,000 processed units, the discount rate per 100,000 units amounts to 8 % × 100,000 / 160,000 = 5 % per functional unit.

While all life cycle costs of Type B components are determined solely by deterministic Type I and Type II costs - and would thus be easy to assess using conventional budgeting techniques - a fundamentally different approach needs to be taken with the Type III costs involved in the use of Type A components and comprising statistically random processes describing the reliability of the component. Its life cycle costs will therefore be assessed using statistical simulation as illustrated by Figure 1.

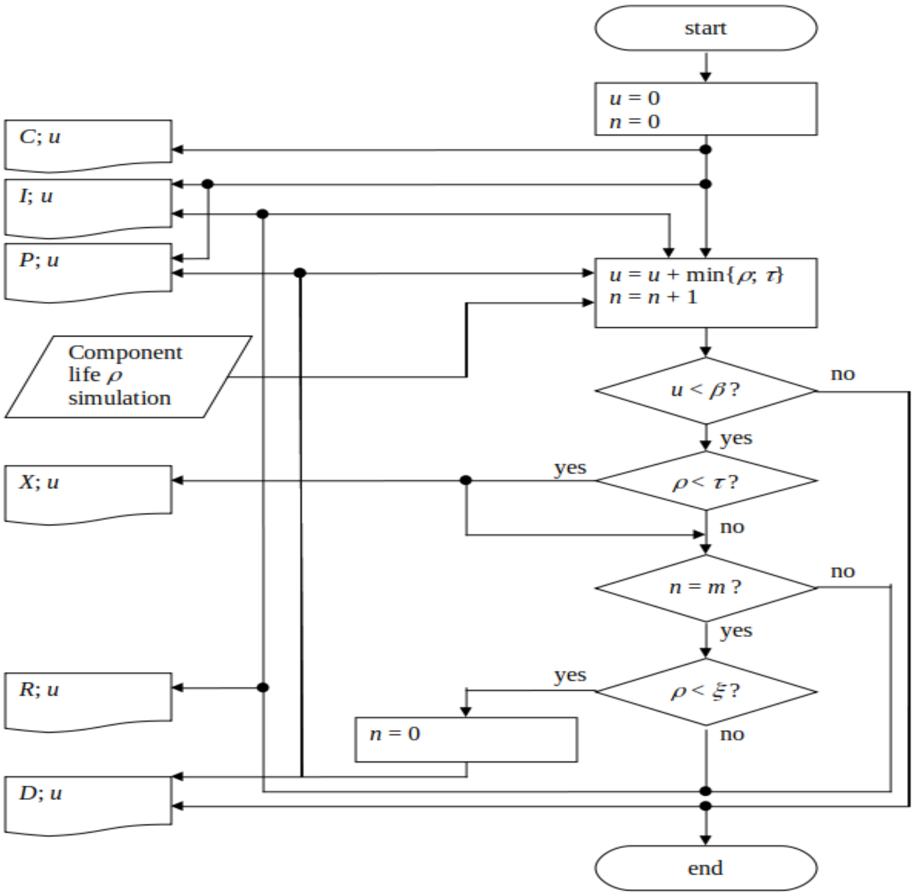

Figure 1. Life cycle simulation run process diagram for Type A component.

3. Results

Decision-making will be based on the functional unit life cycle cost differential of component Type A over Type B, which subtracts the non-operating functional unit costs of the two component types and adds their functional unit operating costs differential as in Equation (1).

$$^{A\text{-}B}LCC = {}^{A}NOC - {}^{B}NOC + {}^{A\text{-}B}OC \quad (1)$$

Using the values listed in Table 1, the non-operating cost per functional unit (i.e. 100,000 processed units) of a Type B component is ${}^{B}NOC$ = € 2,550.

The operating costs differential consists of energy savings and personnel cost savings. Both are in favor of Type A components (this implies a positive value of ${}^{A\text{-}B}OC$). The differential assessment also requires a forecast of the wholesale energy price, which will initially be presumed to be € 60 / MWh. As each of the savings parameters uses different units of measure, they need to be standardized to the functional unit. Power consumption savings then amount to 60 × 1 × 100,000 / 10,000 = € 600 per functional unit and personnel savings to 1,200 × 100,000 / 160,000 = € 750 per functional unit, totaling ${}^{A\text{-}B}OC$ = € 1,350.

The non-operating costs per functional unit of Type A components are generated by statistical simulation, resulting in a random distribution of the functional unit life cycle cost differential between the two component types as illustrated by Figure 2.

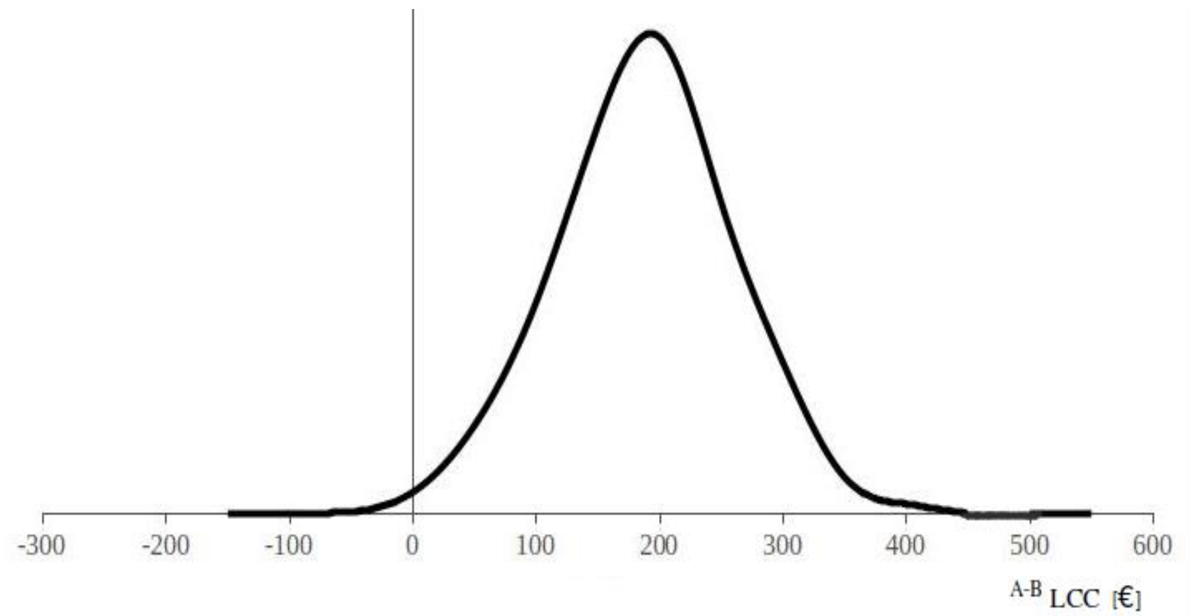

Figure 2. Distribution of the component's life cycle cost differential.

Significantly, the distribution mean is € 153 and its fifth percentile is € 9, which means that the more advanced Type A component outperforms Type B at a 95 % confidence level, and should therefore be preferred.

4. Discussion

The model has been subject to sensitivity analyses in respect to key input parameters and potential operating adjustments. Two parameter forecasts seem critical in terms of potential variable volatility or insufficient information: the exogenous energy price and the endogenous mean life expectation for a Type A component.

Sensitivity analysis clearly indicates that the operating risk due to a potentially shorter component mean life is the more significant one of the two. Even in the rather extreme case of energy prices decreasing by 30 % (i.e. if the price fell down to € 42 / MWh), the use of Type A components would still be merited, while just a moderate increase of the break-down rate resulting in a mean life expectation of 218,000 processed units (down from 250,000 units) would be sufficient to reconsider such a decision.

Conveniently, simulation can also be used to adjust the terms of operation, and thus suggest a means of mitigating this risk. Increasing the scheduled replacement times of the Type A components from 175,000 processed units to 200,000 processed units (assuming there would be no regulatory restrictions to such a mode of operation) would result in a highly positive mean cost differential favoring Type A even under the assumption of its reduced mean life expectancy.

5. Conclusions

Using a case study in the logistics servicing domain, this paper illustrated the applicable potential of combining life cycle costing techniques with statistical simulation in the context of servicing operations and the selection of alternative technological solutions in replacement chain situations. In particular, such an approach makes good sense when the technologies under consideration involve operationally dependent contingent costs, such as the breakdown frequencies analyzed herein. Other applications may similarly involve e.g. servicing time measures or processing feedbacks.

In contrast to conventional capital budgeting, much broader scope of functional system characteristics may be considered within the framework of this methodology, and it is thus viable to integrate aspects of financial and operational analysis in a single decision-making framework. Even though such models are generally suitable for use by industry practitioners, the results must be carefully assessed in terms of input parameters' sensitivities, as well as correct interpretation, which seems to be its main limitation.

References

Broadie Mark, Detemple Jerome. 2004. Option pricing: valuation models and applications. *Management Science*: 50(9), 1145-1177. https://doi.org/10.1287/mnsc.1040.0275

Chang Ching. 2010. *Service systems management and engineering*. Hoboken: John Wiley.

Chen Hong-Yi, Lee Alice, Lee Cheng-Few. 2014. Alternative errors-in-variables models and their applications in finance research. *The Quarterly Review of Economics and Finance*: 58, 213-227. https://doi.org/0.1016/j.qref.2014.12.002

Dhillon Balbir. 2010. *Life cycle costing for engineers*. Boca Raton: Taylor and Francis.

Dui Xiaowei, Zhu Guiping, Yao Liangzhong. 2018. Two-stage optimization of battery energy storage capacity to decrease wind power curtailment in grid-connected wind farms. *IEEE Transactions on Power Systems*: 33, 3296-3305. https://doi.org/10.1109/TPWRS.2017.2779134

El-Akruti Khaled, Zhang Tieling, Dwight Richard. 2016. Developing an optimum maintenance policy by life cycle cost analysis - a case study. *International Journal of Production Research*: 54(19), 5946-5962. https://doi.org/10.1080/00207543.2016.1193244

Favi Claudio, Germani Michele, Campi Federico, Mandolini Marco, Manieri Steve, Marconi Marco, Vita Alessio. 2016. Life cycle model and metrics in shipbuilding: How to use them in the preliminary design phases. *Procedia CIRP*: 69, 523-528. https://doi.org/10.1016/j.procir.2017.11.071

Fulton Lawrence. 2018. Ownership cost comparison of battery electric and non-plugin hybrid vehicles: a consumer perspective. *Applied Sciences*: 8, 1487-1500. https://doi.org/10.3390/app8091487

Hellemo Lars, Barton Paul, Tomasgard Asgeir. 2018. Decision-dependent probabilities in stochastic programs with recourse. *Computational Management Science*: 15, 369-395. https://doi.org/10.1007/s10287-018-0330-0

KPMG. 2019. KPMG Restructuring highlights five sectors facing stress in 2019. Available online: https://home.kpmg/uk/en/home/media/press-releases/2019/01/kpmg-restructuring-highlights-five-sectors-facing-stress-in-2019.html (accessed on 12 December 2019).

Maier Sebastian, Pflug Georg, Polak John. 2019. Valuing portfolios of interdependent real options under exogenous and endogenous uncertainties. *European Journal of Operational Research*: In Print. https://doi.org/10.1016/j.ejor.2019.01.055

Mordechai Shaul. 2011. *Applications of Monte Carlo in science and engineering*. The Hague: InTech.

Mun Jonathan. 2015. *Modeling risk*. 3rd ed., Hoboken: John Wiley.

Norris Gregory. 2001. Integrating life cycle cost analysis and LCA. *The International Journal of Life Cycle Cost Assessment*: 6(2), 118-120. https://doi.org/10.1007/BF02977849

Sinclair David. 2010. Equivalent annual cost: a method for comparing the cost of multi-use medical devices. *Canadian Journal of Anesthesia*: 57, 521-522. https://doi.org/10.1007/s12630-010-9287-3

Vlachý Jan. 2009. Strategie podniku a finanční teorie (Corporate strategy and financial theory). *Politická ekonomie*: 57(2), 147-162. https://doi.org/10.18267/j.polek.678

Vlachý Jan. 2017. The value of innovation in nanotechnology. *Engineering Economics*: 28(5), 535-541. https://doi.org/10.5755/j01.ee.28.5.16770

Vlachý Jan. 2018. Assessing outsourced distribution channels. *Contemporary Economics*: 12(2), 129-138. https://doi.org/10.5709/ce.1897-9254.267

Volkman David. 1997. A consistent yield-based capital budgeting method. *Journal of Financial and Strategic Decisions*: 10(3), 75-88.