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HOW TO SCALE A 3D CONCRETE PRINTING FACILITY? A STOCHASTIC DECISION-SUPPORT FRAMEWORK FOR PRODUCTION INVESTMENT

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***SUMMARY**: The construction sector faces persistent challenges in scaling emerging technologies such as 3D Concrete Printing (3DCP), despite their potential to reduce material waste and accelerate build times. This paper addresses a key barrier to adoption: economic uncertainty in the development and deployment of 3DCP production systems. Drawing on a case study of a commercial 3DCP facility, we develop a three-stage stochastic decision-support framework to guide scaling efforts. The first stage quantifies cost uncertainties in hardware, software, and material systems. The second stage evaluates strategic development pathways under multiple future scenarios. The third stage integrates investment costs to support full cost-benefit assessments. Anchored in the Resource-Based View (RBV), our approach identifies how firms can mobilize technological, financial, and human resources in uncertain environments. Methodologically, we combine Monte Carlo simulations with Simulation Decomposition (SimDec) to enable multivariate cost-benefit analysis. The result is a practical toolkit for managers navigating early-stage innovation in construction production. This research contributes to scholarship on technology adoption, strategic investment under uncertainty, and sustainability transitions in construction.*

***KEYWORDS**: probability distribution, global sensitivity analysis, uncertainty, industrial economics.*

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1. INTRODUCTION

Three-dimensional concrete printing (3DCP) is rapidly emerging as a potentially green-technology for the construction sector (Hassan et al. 2024). By depositing cementitious material layer-by-layer, 3DCP can drastically reduce material waste, shorten build times, and enable highly customised geometries (Hager et al. 2016; De Wolf, Pomponi & Moncaster 2017; Bos et al. 2016). However, both established and early-stage (Startup) firms have multiple barriers to efficient technology development. They often operate in high-uncertainty environments (Tan et al. 2025), have limited historical production and project data (Ayyagari, Chen & García de Soto 2023), and lack structured decision-support tools for such large investment (Taylor & Levitt 2004; Myers 2003; Myers 2016). In addition to this, varying stakeholder misalignments further hinder industry adoption (Walzer et al. 2024b).

Existing literature has extensively covered the technical and environmental advantages of 3DCP, but has often overlooked the economic implications and long-term viability (De Schutter et al. 2018). This oversight extends to integrating 3DCP with advanced construction planning technologies such as Building Information Modeling (BIM), where decision-support tools that address multi-criteria requirements are established (Tan et al. 2021). However, specific studies linking these tools with 3DCP practices are sparse, leaving a gap in holistic decision-support methodologies that accommodate the unique aspects of 3DCP. Previous studies have explored general unit production costs predominantly from the demand side (Cheng 1991), yet comprehensive cost estimation frameworks specifically tailored for 3DCP supply remain underdeveloped (Nagatoishi & Fruchter 2023). While frameworks exist for cost estimation in industrial design products involving economies of scale (Park & Simpson 2005), their applicability to 3DCP has not been empirically validated (Walzer et al. 2024a). Furthermore, existing models either (i) treat cost deterministically, ignoring the stochastic nature of material prices, labour rates, and hardware performance, or (ii) lack a strategic lens that connects resource-based capabilities to investment decisions. Vast literature on uncertainty analysis and strategic decision support provides comprehensive frameworks for risk analysis, but lacks capability of factoring in a multitude of interlinked decisions due to growing combinatorial complexity (Hubbard 2020; Savage & Markowitz 2009; Trigeorgis & Reuer 2017). Without such a framework, firms cannot reliably construct portfolios of development opportunities under said uncertainty.

The pressing question for this study remains: *How can emerging firms navigate uncertainties to adopt 3DCP and enhance their innovative competitiveness in a resource-constrained environment? What type of modeling and simulation is suitable for this task? And how could these results be effectively communicated so that a 3DCP firm can make decisions based on them?*

This study explores the intersection of 3DCP and strategic construction management to develop a non-deterministic framework. This framework aims to help firms navigate technological and economic risks while identifying potential opportunities for growth (Eisenhardt & Martin, 2000; Teece et al., 1997). Consequently, in this paper, we propose a three-stage stochastic decision-support framework:

- Stage 1: Quantify cost uncertainties in hardware, software, and material subsystems using Monte Carlo simulation.
- Stage 2: Evaluate development pathways by embedding “on/off” switches for each resource upgrade and analysing their joint impact with SimDec.
- Stage 3: Conduct a cost-benefit analysis that incorporates investment costs and calculates the breakeven production volume.

The framework is validated with a real world case study of Hyperion Robotics, a Finnish Startup that manufactures water-tanks, foundations, and wall elements via 3DCP. The results deliver a practical toolkit for managers to (i) identify the most influential cost drivers, (ii) prioritize resource upgrades, and (iii) assess economic viability under uncertainty. We adopt a Resource-Based View (RBV) perspective (Barney 1991; Wernerfelt 1984). The rather seminal RBV stresses that a firm’s competitive advantage is derived from the value, rarity, inimitability, and non-substitutability (VRIN) of its tangible and intangible assets. When applied to 3DCP, the RBV suggests that strategic deployment of hardware, software, and material resources can turn a technologically promising process into a financially viable production system.

2. BACKGROUND

2.1 Cost-estimation for emerging construction technologies

Traditional construction cost estimation focuses on whole-project budgets and relies heavily on deterministic spreadsheets (Akintoye 2000; Ranasinghe 1996). Recent literature shows that such approaches under-represent uncertainty in component-level costs, especially for novel processes where historical data are scarce (Dmitrenko et al. 2018). Stochastic methods (Monte Carlo simulation, Bayesian networks, and scenario analysis) have been proposed for prefabrication and modular construction (Gibb & Isack 2003; Eastman et al. 2011) but have not yet been applied in the context of 3DCP. Therefore, previous work developed a probabilistic unit-cost modeling framework for emerging technologies that combined Monte Carlo simulation with Simulation Decomposition (SimDec) to make cost uncertainty, economies of scale, and key cost drivers transparent (Walzer, Kozlova & Yeomans 2024, Walzer et al. 2024a). That work focused on clarifying the unit economics of additive manufacturing in construction on the technology level to help stakeholders understand when and why 3DCP may become cost-competitive. In contrast, this paper builds on the same analytical foundations to support strategic decision-making on a firm level: rather than asking "What does this technology cost?", this study instead assesses "Which strategic choices matter most, under uncertainty, and through which mechanisms do they shape outcomes?" The resulting toolkit shifts the emphasis from technology cost assessment to actionable strategy design under uncertainty.

2.2 Monte Carlo simulation, global sensitivity analysis, and simulation decomposition

Monte Carlo (MC) simulation is a standard approach for analyzing uncertainty in complex models by propagating probabilistic input assumptions to output distributions (Robert & Casella 2004). It allows decision-makers to move beyond point estimates and reason about risks, ranges, and likelihoods of outcomes (Mantha et al. 2025). In most applications, MC analysis focuses primarily on external uncertainty sources, while decision variables are held fixed to reflect factors outside managerial control that nonetheless shape outcomes (Hubbard 2020; Saltelli et al. 2020; Savage & Markowitz 2009). Global Sensitivity Analysis (GSA) complements MC simulation by quantifying how much individual inputs and their interactions contribute to the variance of the model output (Saltelli et al. 2008). By decomposing output uncertainty into attributable sources, GSA identifies the dominant drivers of a model behavior which makes the impacts of uncertainty more transparent. This variance-based perspective enables prioritization by distinguishing influential uncertainties from those with negligible impact. In this context, the recently-developed SimDec procedure combines global sensitivity analysis with a visual decomposition of output distributions (Kozlova & Yeomans 2022) that allows decision-makers to see how groups of inputs jointly shape outcomes. SimDec extends MC and GSA by decomposing simulated output distributions into interpretable sub-distributions associated with combinations of influential input states (Kozlova et al. 2024c). Through visual decomposition, SimDec reveals interaction effects, structurally distinct scenarios, and non-obvious dependencies that are difficult to detect using summary statistics alone. This approach already demonstrated tangible value to applications in multiple business, environmental, and engineering contexts (Kozlova & Yeomans 2024). Open-source implementations in Python, R, Matlab, and Julia, together with a no-code web dashboard, make SimDec readily accessible for practitioners (Roy & Kozlova 2024). Furthermore, uncertainty analysis has traditionally avoided shifting attention from uncertain parameters to decision variables due to combinatorial complexity. However, such a shift is essential for strategic analysis when driven by the needs of a case company. SimDec enables this transition by structuring high-dimensional decision spaces in an interpretable way, making it possible to analyze how alternative strategic choices perform under uncertainty. This a perspective has rarely been, if ever, operationalized in prior work on 3DCP.

2.3 Empirical application in 3DCP

In recent years, 3DCP has emerged as a technology stack in both research and practice (Gardan, Hedjazi & Attajer 2025; Lim et al. 2012). Yet, empirical case studies on the unit economics of 3DCP are still limited (Bischof 2022). Most studies in this nascent field have focused on either technical feasibility (Bos et al. 2016; Le et al. 2012) or environmental impact (Hager et al. 2016), while only a handful have addressed economic decision-making under uncertainty (Graser et al. 2023; Walzer 2025). Consequently, a gap exists for a structured, stochastic decision-support framework that integrates RBV insights with SimDec-based sensitivity analysis for production-investment planning as described above.

3. METHODOLOGY

3.1 Case-study design

The integration and development of 3DCP technologies within a construction firm are examined through a single-case study approach that provides deep, context-rich insights into the complex processes of adopting and adapting new technologies in a unique organizational setting (Yin 2018; Eisenhardt 1989; Eisenhardt and Graebner 2007). This methodology focuses on understanding the organizational adaptability and contextual awareness required for effective technology integration (Hargadon and Douglas 2001; Siggelkow 2007). Case studies are particularly useful in construction-management research because they comprehensively capture real-world phenomena operating within their natural context (Taylor et al. 2010). Cases allow researchers to explore the intricacies of implementation by incorporating both qualitative and quantitative data (Cheng 1991) into robust theoretical models (Yin 2018). This study adheres to these principles by employing a structured data-collection and analysis protocol to ensure the robustness of the findings. Through the study of Hyperion Robotics, a Finnish Startup that manufactures water-tanks, foundations, trenches and wall elements via 3DCP (Figure 2), the research aims to (i) identify critical factors influencing the integration of 3DCP technologies, and (ii) develop actionable insights that can inform broader industry practice. Thus, we propose a multi-staged analytical framework (Figure 1).

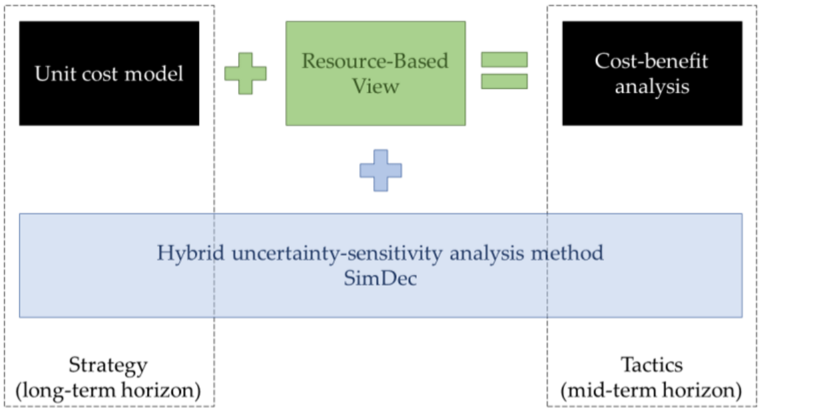


Figure 1: The proposed multi-stage analytical framework.

3.2 Empirical context and case description

Hyperion Robotics (Hyperion 2024) was founded in 2019 and has grown rapidly due to public funding and venture-capital investments that recognise the potential of its sustainable-construction approach. The firm operates a micro-factory in Espoo, Finland (Figure 2, left) that produces water-tanks, foundations, trenches and wall elements through 3DCP (Figure 2, right).

Table 1: The three stages of the analysis.

Stage	Question	Model	Inputs to hybrid uncertainty-sensitivity analysis method SimDec
1	Which sources of uncertainty/variation drive the unit cost?	Existing deterministic spreadsheet model of the case company that computes unit cost.	Numerical properties of the process
2	Which development opportunities produce the most benefit?	Updating the existing model by embedding the effects of the development opportunities via a selection tool.	Selection tool elements
3	Which development opportunities make sense to implement first from the short-term economic viability viewpoint?	Updating the Stage 2 unit cost model with investment costs to conduct a cost-benefit analysis.	Investment cost, selection tool elements

Figure 2: 3DCP Workspace in Espoo, Finland (left) and Infrastructure Foundation Products (right). Image courtesy of Hyperion Robotics (2022, 2025).

The studied firm presents a compelling case for exploring the development of decision-support mechanisms to customize 3DCP offerings, aligning them with organizational goals and operational constraints. The decision problem faced by the company is approached in the three stages outlined in Table 1.

3.2.1 Unit-Cost Modelling

The accurate estimation of component costs is a complex task influenced by a multitude of external and internal factors, making heuristic methods insufficient (Horngren et al. 2010). External factors such as supply chain dynamics, commodity price fluctuations, and market demand, along with internal factors including process stability, prototype testing, and human considerations, contribute to the uncertainty and variability in unit cost estimates (Chopra and Meindl 2001; Curran et al. 2004). Given this complexity, the model's level of detail needs to align with the company's stage, processes, and decision-making context. Consequently, we present an empirical model incorporating actual values from a real-world production project within the case firm. This model includes basic equations, such as the one depicted below, which outlines the structure of the initial unit cost model.

$$Unit\ cost\ [€] = \frac{labor\ cost + materials\ cost + consumables\ cost + equipment\ cost}{units\ produced} \tag{1}$$

Equation (1) demonstrates fundamental costing principles. By breaking down the unit cost into its constituent components, this equation provides a clear initial framework for understanding and managing the various cost drivers involved in the production process. It also ensures that the model's granularity accurately reflects both current operational realities and strategic needs.

3.2.2 Modelling of development opportunities

Table 2 categorizes the innovation into three distinct areas: materials, software, and hardware. Each developmental opportunity is evaluated against a standard baseline consisting of Material 1.1 and the current 3DCP process baseline to determine outputs such as unit cost. The table presents several prospective opportunities for material development, including various material combinations that may require specific hardware enhancements. It is important to note that Environmental Product Declarations for these materials are currently unavailable, as they have not yet been fully developed or tested. Additionally, the table outlines potential advancements in hardware, highlighting expected benefits such as increased deposition speeds and reduced interruptions during the printing process. Finally, the table discusses two software enhancement opportunities and their anticipated effects.

3.2.3 Monte Carlo-based Simulation Decomposition

The method for the model analysis chosen in this study is a hybrid sensitivity-uncertainty approach called Simulation Decomposition or SimDec (Kozlova et al. 2024c). SimDec consists of the computation of sensitivity indices (the global sensitivity analysis component) and a visualization based on a novel decomposition procedure (the uncertainty analysis element). The rationale behind both components and their algorithmic procedures are described in this section. Models are only useful for decision-making when their solution space is properly explored because only then can the combined effect of uncertainties and managerial actions be elucidated upon (Saltelli et al. 2019). The estimation of the importance of different factors when all the moving parts of the model are altered simultaneously is the pinnacle of the global sensitivity analysis field. Various families of global sensitivity analysis methods have been under active development and evaluation (Pianosi et al. 2016). One of the most straightforward global sensitivity analysis methods created for computing sensitivity indices is the "simple binning approach" of Kozlova et al. (2025). Binning methods are computationally efficient and extremely accurate (Marzban & Lahmer 2016; Kucherenko et al. 2017), and also capable of capturing the impacts from inherent` dependencies in the input variables, an important feature for the analysis of complex models (Kucherenko et al. 2017; Kozlova et al. 2025). The simple binning approach for sensitivity indices is a variance-based sensitivity analysis, which estimates the contribution of (groups of) input variables to the variability of the output. In practice, it involves the estimation of conditional variance in accordance with the classic formulation of Sobol' indices. In the simple binning approach, the estimation of indices is implemented by binning the X_i, computing the averages of Y in each bin of X_i, taking the variance of those averages, and scaling this conditional variance by dividing by the overall variance of the output.

$$S_{X_i} = \frac{Var(\mathbb{E}(Y|X_i))}{Var(Y)} \tag{2}$$

Furthermore, in the subsequent analysis, the individual (first-order) and pair-wise (second-order) effects of input variables are amalgamated to produce a combined, or closed, sensitivity index for each variable. The detailed procedure and tests of its performance are presented in Kozlova et al. (2025). However, identifying which specific variables are important represents only a partial exposition of the underlying impacts. It has been shown that input variables, and most especially interactions from their combinations, can produce intricate effects of different shapes on the output variable. The nature of the shapes of these relationships critically influences the insights for decision-making (Kozlova et al. 2024c). A rare visualization pattern can reveal clear insights from multidimensional data and SimDec has proven uniquely capable for uncovering such revelations (Kozlova, Lo Piano and Yeomans 2024a). SimDec partitions the data into scenarios comprised of combinations of the ranges of the most important input variables and then visualizes the decomposed distribution of the output variables as stacked histograms, box plots or scatter plots. The input variables for decomposition are ordered by the magnitudes of their corresponding sensitivity indices. The most important input variable goes first and its ranges partition the output distribution into the most distinct subdistributions. This visualization is further enhanced by the coloring procedure, which assigns distinct primary colors to the subdistributions produced from the most important input variable, with shadings of these main colors applied to any further variable partitions. The specific scenario ordering and coloring procedures in a decomposition are structured to ensure the most meaningful visual outcomes (Alam et al. 2023). Initially introduced as a visualization-only procedure (Kozlova, Collan & Luukka 2016; Kozlova & Yeomans 2022), SimDec was later transformed into a global sensitivity analysis-based procedure for the automatic detection and selection of the most important input variablesComplete details on all algorithms, their usage, and resulting interpretation can be found in Kozlova et al. (2024b).

3.2.4 Cost-Benefit Analysis and Choice of Profitability Indicator

Multiple methods, including payback period, net present value (NPV), and breakeven production volume, were considered for evaluating the investment options of the Hyperion case. The payback period method calculates the time required for unit cost savings to recoup the investment. Despite its relative simplicity, this approach hinges on assumptions about annual production volume, which can vary across development options and be technically constrained. Furthermore, it risks double-counting production volumes already included in unit costs. The major drawback is its disregard for the time value of money and any cash flows beyond the breakeven point, thereby providing a somewhat incomplete picture of investment profitability (Akintoye 2000; Myers 2003). Conversely, Net Present Value (NPV) lays out future cash flows for each development scenario, providing a comprehensive assessment by accounting for varying production volumes. Although detailed and robust, NPV requires extensive data and effort, which may be challenging given the current dataset's limitations. NPV's strength lies in its ability to incorporate the time value of money by discounting future cash flows to their present value. However, its reliability depends heavily on the complex task of accurately estimating the discount rate (Brealey et al. 2011; Hager et al. 2016). Although the first two methods possess numerous unique strengths and limitations, the breakeven production volume was deemed most appropriate to represent the complex context of the case and the level of knowledge regarding its financial assumptions. In contrast to NPV (which requires assumptions on the discount rate, the production volumes for several years ahead, and the time horizon), breakeven analysis requires no additional assumptions (Needles et al. 2011). The breakeven quantity of units simply shows how many units need to be manufactured before the savings from unit cost reduction pay off the initial investment (3) (Garrison et al. 2021).

$$Breakeven\ quantity\ [units] = \frac{investment\ cost\ [€]}{unit\ cost\ reduction\ [€]} \tag{3}$$

This calculation assumes a single product type and presumes that its market price remains unchanged, regardless of the material or production method applied. If either the product mix or the selling price shifts because of the investment, the breakeven quantity becomes less meaningful as a basis for decision-making.

Table 2: Development opportunities of the case company. Source: Hyperion Robotics.

Innovation Category	**Development opportunity**	**Description**	**Anticipated Effect**			
			Price, €/ton	**CO_2, kg/ton**	**Comment**	**Implementation cost**
Material	Material 1.1	Baseline material v1	440	173		0
	Material 1.2	Baseline material v2	-19%	-2%		20k
	Material 1.3	Baseline material v3	-32%	-23%	- only available with ***Hardware 1***	40k
	Material 2.1	Alternative	-23%	-61%		30k
	Material 2.2	Alternative	-29%	-117%		120k
	Material 3	Alternative	-2%	-70%		30k
	Material 4	Alternative	-49%	-95%		30k
	Material 5	Alternative	+6%	-154%		80k
	Material 6.1	Alternative	+45%	N.A.	- only available with ***Hardware 5***	40k
	Material 6.2	Alternative	+26%	N.A.	- only available with ***Hardware 5***	40k
	Material 6.3	Alternative	+14%	N.A.	- only available with ***Hardware 5*** - only available with ***Hardware 1***	40k
Hardware	Hardware 1	Mixer Upgrade			- ***Self-compacting concrete*** to minimum - enables cheaper versions of ***Material 1.3 and 6.3***	70-90k
	Hardware 2	End-Effector v1			- minus one robot operator ***person***	50k
	Hardware 3	End-Effector v2			- ***Waste mortar/buffer*** reduced to 10% - ***Halts during the print*** reduced to 50% - ***Space constraint*** to 4 units per day	100k
	Hardware 4	Robot Upgrade			- ***Space constraint*** to 6 units per day	200-300k
	Hardware 5	Pump Upgrade			- ***Pre-print time*** to 0 - ***Printing Halts*** to 25% - ***Waste mortar/buffer*** to 10% - two ***persons*** less - ***Productivity*** to 100%	80k-100k
	Hardware 6	Rebar Upgrade			- Printing Halts to 50% - one ***person*** less - ***Productivity*** to 80%	100k-150k
Software	Software 1	Print Speed			- ***Productivity*** 50% higher	25k
	Software 2	Software Library			- ***Pre-production*** twice faster	200k

3.2.5 Benefits of Using SimDec for Uncertainty Considerations in Cost-Benefit Analysis

Traditional valuation methods with profitability indicators (including all those considered above) are deterministic and overlook uncertainty. The binary decision rule of NPV (invest only if positive) restricts strategic design freedom (Trigeorgis 1996). To overcome the determinism of financial modeling, real option valuation methods have been introduced to capture uncertainty and recognize the value of flexibility (Mun 2006). However, real options still rely on a deterministic threshold, rendering them a binary decision-making framework, also.

SimDec generates much richer information and actionable decision-making insights in cost-benefit analysis by integrating uncertainty analysis directly into global sensitivity analysis (Kozlova et al. 2024c). Manually investigating the impact of single development opportunities would require thousands of iterations and result in a disorganized process with lost insights. Conversely, SimDec computes importance indices for all possible combinations of development opportunities and can guide decision-makers towards the most critical developments by effectively visualizing the system relationships.

4. RESULTS

This section describes the outcomes of the three-stage analysis approach used to evaluate the unit cost model of the case company. The first stage determines which sources of uncertainty or variation most significantly impact the unit cost. By employing SimDec on the existing deterministic unit-cost model, we translate the variation of input parameters into the variability of the output. This analysis highlights the key drivers of unit cost variability. The second stage assesses various development opportunities by updating the model with an on/off checkbox for Hardware and Software and a selection list for Materials that codes these effects with specified constraints (see Table 2 for constraints). SimDec is utilized to evaluate how these opportunities impact the output. This enables us to identify which combinations of upgrades provide the most significant cost reductions and performance improvements. The third stage focuses on determining which development opportunities should be implemented first based on short-term economic viability. This involves updating the Stage 2 model by incorporating investment costs into a cost-benefit analysis. The analysis prioritizes development options and balances long-term benefits against initial investment costs in order to identify feasible short-term improvements.

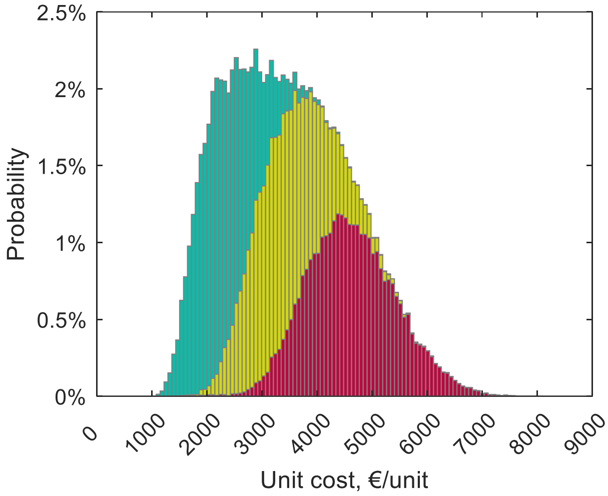
4.1 Stage 1: Assessing drivers behind the unit cost

Table 3 presents the variation ranges for the model input variables identified by Hyperion together with their corresponding sensitivity indices computed by the simple binning algorithm.

Table 3: Variation in the input variables and their respective effect on the model output.

Input variable	Uniform distribution		Sensitivity index
	min	max	
Idle time, h/day	2	5	1%
Printing productivity of 1 robot, tons/h	2	4	1%
Productivity of the robotic system	60%	100%	2%
Material savings - design optimization	25%	75%	75%
Percentage of printed mortar of total volume	20%	70%	0%
Material price, €/ton	Discrete from Table 2		8%
Chemical admix, €/pack	25	50	1%
Waste mortar/buffer	10%	100%	8%
Self-compacting concrete, €/m^3	300	1000	5%
Steel reinforcement, €/kg	2	5	1%

Although, a priori, several model inputs were presumed influential by Hyperion, only Material savings provided a significant contribution to the output variability (explaining 75% of the unit cost variation). Material price, Waste mortar/buffer, and Self-compacting concrete appear somewhat influential. All of the remaining input variables exhibit only negligible influence on the unit cost. Consequently, the visualization is constructed by decomposing only on the most significant input, Material savings (Figure 3). The Figure exposes a monotonic relationship in which higher material savings naturally produce less expensive units.



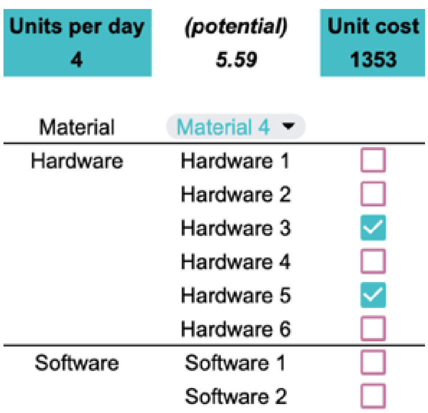
Color	Material savings	Unit cost, €/unit		
		min	mean	max
(red)	Low 25-42%	1 349	4 588	8 069
(yellow)	Medium 42-58%	1 443	3 444	6 383
(teal)	High 58-75%	975	2 316	6 810

Figure 3: The Decomposition of Unit cost [€/unit] by Material savings explains 75% of the variation and is based on the existing unit cost model.

The SimDec visualization in Figure 3 and the sensitivity indices in Table 3 reveal the fairly simple mechanics underlying the model, in which it can be observed that the Unit cost output is monotonically dependent on only the single most influential input.

4.2 Stage 2: Evaluation of development opportunities

Unit cost cannot be reduced directly by any of the identified input variables, but only through the concurrent implementation of certain specific developments. To make this analysis actionable, the set of available development opportunities and their corresponding effects on the unit cost drivers (Table 2) have to be integrated into the model. However, embedding development opportunities into the model considerably modifies the entire logic of the model mechanics. Consequently, a selection tool was built to enable switching different development opportunities on-and-off and for selecting a desired material, Figure 4.



Units per day	*(potential)*	Unit cost
4	*5.59*	1353
Material	Material 4	
Hardware	Hardware 1	☐
	Hardware 2	☐
	Hardware 3	☑
	Hardware 4	☐
	Hardware 5	☑
	Hardware 6	☐
Software	Software 1	☐
	Software 2	☐

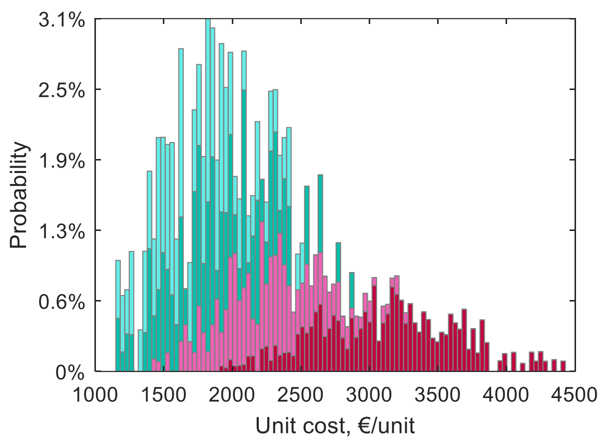
Figure 4: The selection tool in the spreadsheet environment.

The numeric inputs in the model then became functions of these newly-introduced switches. To incorporate these changes, several constraints need to be implemented, including: (i) space constraints of printing a maximum of 2 units per day, which can be lifted by Hardware 3 and Hardware 5; (ii) a constraint on the group of Materials 6 that only becomes available with Hardware 5; and (iii) a constraint on cheaper versions of materials, Materials 6.3 and Materials 1.3, enabled only by Hardware 1. The total number of unique combinations of the 8 development options and 11 materials is 2^8*11 = 2,816 (neglecting constraints). A separate indicator is introduced into the model to signify whether each random combination of development options fulfills all of the constraints. The model was simulated 10^5 times. Infeasible simulation runs that do not satisfy the constraints (about a quarter of the dataset) were filtered from further analysis. The resulting data was used in the SimDec procedure for computing the global variance-based sensitivity indices in Table 4 and the follow-up visual decomposition in Figure 5.

Table 4: Global sensitivity indices computed from the simulation of the upgraded model.

Input variable	Sensitivity index
Material (all, as aggregate)	21 %
Hardware 1	3 %
Hardware 2	1 %
Hardware 3	17 %
Hardware 4	1 %
Hardware 5	54 %
Hardware 6	3 %
Software 1	2 %
Software 2	0 %

Table 4 shows that only three inputs significantly influence the global solution space when everything changes: Hardware 5, Hardware 3, and Material. Figure 5 presents the decomposition of the unit cost by the presence or absence of Hardware 3 and Hardware 5 and by Material in Figure 6.



Color	Hardware 5	Hardware 3	Unit cost, €/unit min	mean	max
	No	No	1 914	3 106	4 413
		Yes	1 411	2 247	3 254
	Yes	No	1 133	1 893	2 845
		Yes	1 133	1 757	2 499

Figure 5: The unit cost is divided between Hardware 5 (54% importance) and Hardware 3 (17% importance) and is based on the unit cost model that includes the effects of development opportunities.

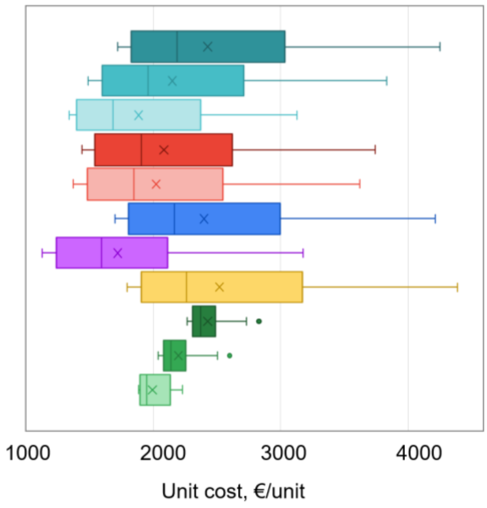
An implementation with Hardware 5 provides the most significant development as it drives the unit cost down noticeably under any circumstances (compare cyan color versus magenta in Figure 5). Hardware 3 reveals a more heterogeneous effect in that it improves the unit cost noticeably when Hardware 5 is not implemented (light magenta subdistribution is shifted to the left compared to dark magenta) but has a less pronounced effect if Hardware 5 is already in place (light and dark cyan subdistribution are on top of each other). This outcome can be explained by the partially overlapping effects of the two development options. The same distribution of unit cost is then decomposed by Material (Figure 6). Due to the larger number of subdivisions (eleven materials), the decomposition is easier to read in boxplot form in comparison to a histogram. The same data, with the same decomposition along the same X axis, is presented, with the only difference being that the scenarios (Material types) are visualized not as series in a stacked histogram, but as boxes in the boxplot.

The effect of Material on unit cost is dictated mainly by its price. The cheapest, Material 4, has the lowest unit cost (most-left box). This Material also has the lowest emissions, which makes it an attractive option. The group of Materials 6.1-6.3 results in lower and narrower subdistributions of unit costs. This happens because they only become available with Hardware 5, which drives the unit cost down due to its compound effect. The choice of Material, however, also depends on the construction project's and element's specifications. Thus, choosing which Materials to develop depends upon the perceived market for the respective structures. Although SimDec highlights the two best development opportunities, observing deterministic scenarios might also prove beneficial for planning the order of development projects with resource constraints. Table 5 contrasts the individual effect of each development opportunity to the base case where no developments are implemented.

Table 5: The deterministic effect of development opportunities on unit costs and space use for the base case.

Development opportunities	**Unit cost, €/unit**	**Space use, units/day**
Material 1.1, no developments, space constraint two units/day	4277	1.01
Single development opportunities		
Hardware 1	3845	1.01
Hardware 2	4087	1.01
Hardware 3	3179	1.08
Hardware 4	4277	1.01
Hardware 5	2295	2.00
Hardware 6	3665	1.44
Software 1	3716	1.52
Software 2	4206	1.06
Hardware combinations		
Hardware 5 + Hardware 3	1949	4.00
Hardware 5 + Hardware 4	1851	5.59
Hardware 5 + Hardware 3 + Hardware 4	1851	5.59
Compounding with cheaper material		
Hardware 5 + Hardware 3 + Hardware 1	1840	4.00
Hardware 5 + Hardware 3 + Hardware 1 + Material 1.3	1456	4.00
Hardware 5 + Hardware 3 + Material 4	1353	4.00
Compounding with other developments		
Hardware 5 + Hardware 3 + Material 4 + Hardware 6	1353	4.00
Hardware 5 + Hardware 3 + Material 4 + Software 1	1353	4.00
Hardware 5 + Hardware 3 + Material 4 + Software 2	1353	4.00

Table 5 illustrates the distinctive effect of Hardware 5, which almost halves the unit cost. Moreover, that is the only option with a binding space constraint. Thus, implementing development options that enable more space is especially relevant to boost the effect of Hardware 5. Only two developments expand the space, Hardware 3 and Hardware 4. The combination of Hardware 5 and Hardware 4 provides results that are not as good as those of Hardware 5 and Hardware 4 alone. All three together, however, give the same result as [Hardware 5 + Hardware 4], so implementing both space enlargement developments is not economically viable. The choice between Hardware 3 and 4 would depend on how many resources their implementation requires; Hyperion's preliminary estimation suggests that Hardware 4 might be too expensive, thereby favoring the combination [Hardware 5 + Hardware 3]. A cheaper Material 1.3 can be enabled with Hardware 1, which brings the unit cost further down, but the cheapest Material 4 without any new hardware required improves the unit cost even more. Further, compounding the combination of these development options [Hardware 5 + Hardware 3 + Material 4] does not affect the unit cost due to the binding space limit. To marginally improve the situation, software developments should only be selected if either Hardware 5 development is impossible (or substantially delayed) or if some other developments to extend space are available. The possible path of development is illustrated in Figure 7.



Color	Material	Unit cost, €/unit		
		min	mean	max
	Material 1.1	1 729	2 440	4 277
	Material 1.2	1 497	2 162	3 855
	Material 1.3	1 345	1 895	3 147
	Material 2.1	1 447	2 095	3 764
	Material 2.2	1 378	2 034	3 639
	Material 3	1 707	2 410	4 237
	Material 4	1 133	1 729	3 193
	Material 5	1 804	2 534	4 413
	Material 6.1	2 279	2 441	2 845
	Material 6.2	2 047	2 209	2 613
	Material 6.3	1 895	2 003	2 243

Figure 6: Decomposition of the unit cost by Material (21% importance).

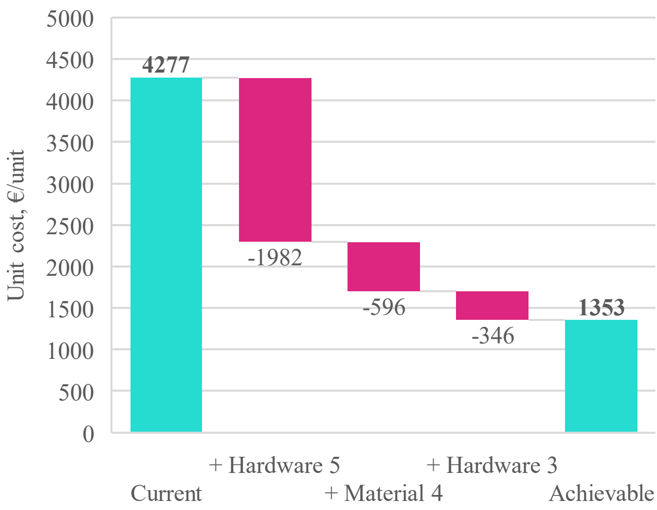


Figure 7: Unit cost under one possible development strategy.

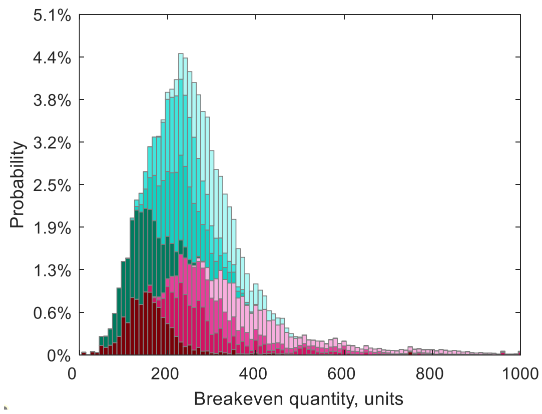
4.3 Stage 3: Cost-benefit analysis

While the unit cost alone provides a good strategic evaluation of the development opportunities, it neglects the project's shorter-term tactical considerations involving the different investment costs. The inclusion of investment costs is key to embracing the resource-based view. The analysis includes the investment cost (Table 3) by computing the breakeven quantity of units to be manufactured before the investment cost pays off (see equation 3). This calculation is added to the model and is repeatedly simulated 10^5 times with the same input assumptions as before. In addition to filtering out the simulation runs that were not fulfilling the constraints, the outliers resulting from too low a denominator for equation (1) were also removed. The resulting sensitivity indices show a different importance profile in comparison to that of the unit cost (Table 6).

Table 6: Global sensitivity indices show the importance of development options for the breakeven quantity of units (the third column) contrasted with the earlier computed sensitivity indices for the unit cost (the second column).

Input variable	Sensitivity index for the unit cost (Table 4)	Sensitivity index for the breakeven quantity of units
Material (all, as aggregate)	21 %	12 %
Hardware 1	3 %	1 %
Hardware 2	1 %	0 %
Hardware 3	17 %	9 %
Hardware 4	1 %	15 %
Hardware 5	54 %	23 %
Hardware 6	3 %	2 %
Software 1	2 %	1 %
Software 2	0 %	11 %
Investment cost	-	17 %

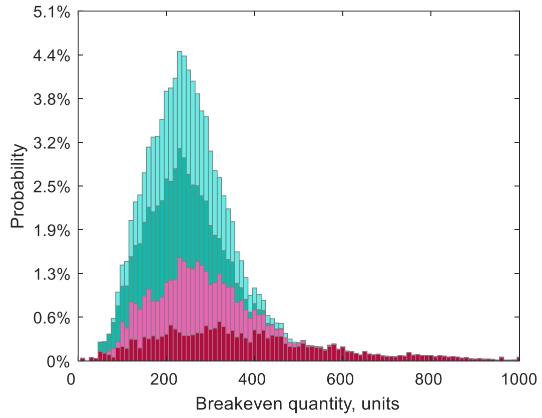
Investment costs (essentially the denominator in the computation) play a role in the variability of the breakeven quantity (17% importance). Hardware 5 retains its dominant position of influence, although diminished to 23% from 54%. Considering its relatively low investment cost (Table 1), this finding can be attributed to its critical positive effect in reducing unit costs. Hardware 4 and Software 2 transform their previous negligible indices into more influential values for the breakeven quantity of the unit cost (15% and 11%, respectively). This is clearly due to the high investment costs that drive the negative effect. The decomposition of these three development opportunities is presented in Figure 8.



Color	Hardware 5	Hardware 4	Software 2	Breakeven quantity, units		
				min	mean	max
	No	No	No	-	162	742
			Yes	151	301	990
		Yes	No	158	339	1000
			Yes	246	452	1000
	Yes	No	No	41	141	282
			Yes	120	228	383
		Yes	No	105	229	410
			Yes	171	308	519

Figure 8: The breakeven quantity of units needed to pay off the investment costs is decomposed by Hardware 5 (23% importance), Hardware 4 (15% importance), and Software 2 (11% importance).

Figure 8 confirms the positive effect of the Hardware 5 implementation on the breakeven quantity (if implemented, fewer units need be produced to pay off the investment, blue scenarios) and the negative effects of Hardware 4 and Software 2 (with their implementation, the breakeven quantity grows; the lighter shades are shifted to the right). These results favor the implementation of Hardware 5 as soon as possible. They also suggest delaying the implementation of Hardware 4 and Software 3 until higher production volumes can be achieved to pay off these investments faster. Another decomposition can be constructed using only the positively affecting unit costs development options. These specific development options are Hardware 5 and Hardware 3, even though the latter did not yield a high sensitivity index for the breakeven costs (Figure 9).



Color	Hardware 5	Hardware 3	Breakeven quantity, units min	mean	max
	No	No	0	371	1 000
		Yes	70	256	621
	Yes	No	41	212	458
		Yes	72	242	519

Figure 9: The breakeven quantity of units to pay off the investment costs decomposed by only the positively affecting unit cost development options, Hardware 5 (23% importance) and Hardware 3 (9% importance).

As with the unit cost, the implementation of Hardware 3 only significantly affects the breakeven quantity if implemented when the Hardware 5 is not in place (compare dark red and light red scenarios). If Hardware 5 has already been implemented, however, then Hardware 3 does not produce noticeable differences to the breakeven quantity (compare dark blue and light blue shades). The same decomposition logic in Figures 5 and 9 enables a contrasting of these two outputs via a scatterplot on a single visualization, Figure 10.

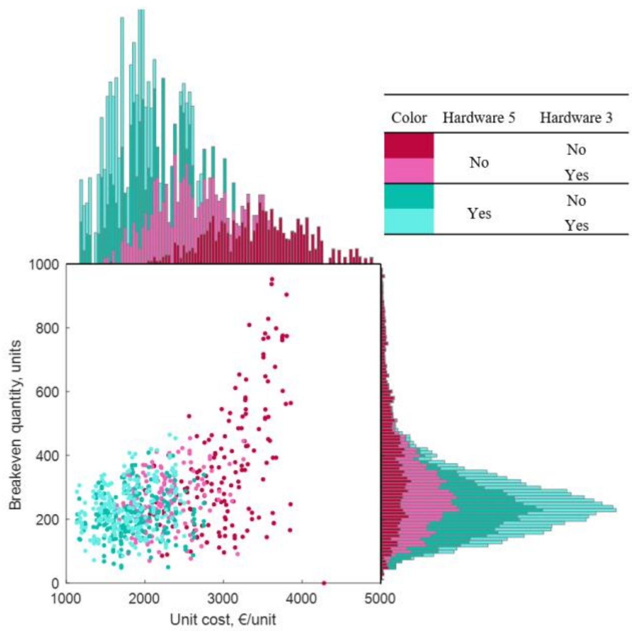
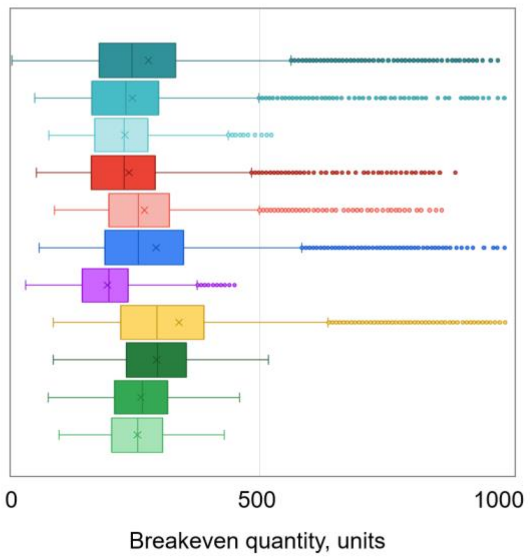


Figure 10: The relationship between the breakeven quantity of units and the unit cost while decomposed by the implementation of Hardware 5 and 3.

Figure 10 exposes a clear monotonic relationship between unit cost and breakeven quantity. The scatter plot shows only every 100th simulation run to avoid overcrowding. The histograms correspond to the earlier Figures 5 and 9. The unique visualization provided by the scatterplot makes the decision-making exercise straightforward, since the strategic and tactical indicators do not conflict with each other. Namely, implementing Hardware 5 and Hardware 3 provides benefits from both lower unit cost and fast payoff. The breakeven quantity's Material also contributes a smaller, but distinctly visible, role (12% importance). Its decomposition is presented in boxplot form in Figure 11.



Color	Material	Breakeven quantity, units		
		min	mean	max
	Material 1.1	0	276	990
	Material 1.2	45	244	997
	Material 1.3	75	229	527
	Material 2.1	49	237	904
	Material 2.2	86	268	870
	Material 3	55	292	997
	Material 4	28	193	451
	Material 5	84	338	1 000
	Material 6.1	84	293	519
	Material 6.2	73	261	460
	Material 6.3	95	254	430

Figure 11: Decomposition of the breakeven quantity of units by Material (12% importance).

When the unit cost of materials is combined with their investment cost to arrive at the breakeven quantity of units, much less difference occurs between material types, since the majority of data in each scenario overlaps (boxes occupy similar ranges), which also manifests in the lower sensitivity index (12% importance compared to previous 21%). The exception is Material 4, which combines a moderately low investment cost and the lowest unit cost, resulting in the lowest breakeven quantity of units, with the lowest average, below 200 units, compared to other materials. Once again, the strategic and tactic advice material-wise is not conflicting, favoring Material 4 for the most pronounced unit cost reduction and fast payoff.

4.4 Key findings

Material-saving potential explains 75 % of the variance in unit cost, while the most impactful hardware upgrade (Hardware 5) accounts for 54 % (Table 4). From an RBV perspective, the ability to secure cheaper binders is a rare and inimitable resource that directly lowers production cost. Hardware 5 halves the mean unit cost and reduces the breakeven quantity by 60 % (Figure 10). However, additional upgrades show diminishing returns because their effects overlap.

5. DISCUSSION

The central phenomenon of this study is the uncertain economic scalability of 3D concrete-printing (3DCP) facilities. Companies that plan to move from a pilot plant to commercial-scale production must decide which hardware, software, or material upgrades to finance while confronting large uncertainties in input costs, labour rates, and market demand. The existing literature either presents deterministic unit-cost models (e.g., De Schutter et al. 2018) or focuses on technical performance (Hassan et al. 2024). Consequently, thus far, decision-makers have lacked a tool that (i) quantifies uncertainty, (ii) highlights the most influential levers, and (iii) translates these insights into a clear investment-payoff metric. We address the gap with a three-stage stochastic decision-support framework that is explicitly linked to the seminal RBV (Barney 1991) and its VRIN extension (Wernerfelt 1984). The stages are to:

- Identify Sources of Uncertainty in Unit Cost (Stage 1): The existing deterministic spreadsheet model was used to identify numerical properties and sources of uncertainty.
- Determine Beneficial Development Opportunities (Stage 2): The model was updated by embedding development opportunities via a selection tool, introducing dynamic elements reflecting potential changes.
- Assess Short-term Economic Viability (Stage 3): Investment costs were integrated into the updated model from Stage 2 to conduct a cost-benefit analysis.

The methodological core, which is a Monte-Carlo simulation coupled with SimDec (Kozlova et al., 2024), extends the prescriptive-analytics work of Bertsimas & Kallus (2020) and provides a transparent attribution of cost reductions to individual levers present in the case study firm.

5.1 Limitations and future work

We employed the breakeven production volume method as it is most appropriate for the current level of understanding and empirical context. While methods such as NPV and payback period are valid, they would not likely provide additional insights to this setting. The selection of the breakeven method reflects the company's size, level of development, and personnel expertise rather. Additionally, this study analyzed a single component, which does not fully represent the range of variability found in construction or infrastructure projects. Several important extensions such as the level of prefabrication, inventory management, and logistics were not included in this study. Future research can fine-tune our newly established framework to other case companies to extend its general applicability and overall robustness. In future research, there is also a need for increased collaboration between academia and industry to ensure that theoretical advancements can be effectively translated into practical tools and techniques that can be readily adopted by construction professionals. Furthermore, action research studies could potentially close the feedback loop by nurturing theory development in the areas of decision-making and knowledge management. Yet, the presented study highlights the synergies that can be achieved by integrating a real-world company-dictated problem into state-of-the-art academic developments rooted in simulation techniques.

Since 3DCP technologies promise substantial reductions in waste and carbon emissions (Bos et al. 2016; Le et al. 2012), integrating environmental considerations into economic analyses is vital for sustainable development. However, the current state of CO2 data highlights a gap in our understanding of the full environmental impact of 3DCP, which must be addressed to fully validate its sustainability claims. Although our study data lacked comprehensive Environmental Product Declarations for all materials, recognizing this gap could provoke future research. While we assumed informed choices about existing valuation methods, future research could incorporate the additional implications of CO2 emissions and circular business models. Understanding the effects of carbon taxation and carbon offsets into circular business models could contribute additional valuable insights for sustainable development (Geissdoerfer et al. 2018). Such future work would align with the broader environmental goals discussed earlier in the paper. Lastly, to increase industry adoption, further considerations of varying stakeholder perspectives (see Walzer et al. 2024; Walzer 2025; Wu et al. 2024) and should be integrated into such decision-making processes.

6. CONCLUSIONS

We demonstrate that a rigorously quantified, resource-based framework can steer the scaling of 3DCP facilities when cost and performance parameters are highly uncertain. Embedding binary development-opportunity switches into a Monte-Carlo engine and applying variance-based SimDec reveals that material-saving strategies explain 75 % of the output variance, while the hardware upgrade “Hardware 5” accounts for 54 %. When investment costs are introduced, Hardware 5 cuts the breakeven production volume by about 60 %, which transforms a costly capital outlay into a manageble pay-back that creates immediate value for the firm. According to the resource-based view, low-cost, high-performance binders constitute a valuable, rare, and hard-to-imitate resource (Barney 1991) that delivers a clear cost advantage. Hardware 5 enlarges the printable footprint and raises deposition speed, thereby enhancing the firm’s dynamic capabilities, the ability to reconfigure resources swiftly in response to market signals (Teece 1997). Because the stochastic framework quantifies uncertainty, it removes the opacity inherent in deterministic spreadsheet models that often leads to sub-optimal investment choices (De Schutter et al. 2018).

We contribute three advances that fill notable gaps in construction-management research: (i) a methodological bridge that links RBV theory with stochastic simulation that addresses the paucity of uncertainty-aware strategic tools; (ii) empirical evidence that quantifying uncertainty reshapes technology-adoption priorities, responds to calls for data-driven decision support (Tan et al. 2025); and (iii) a lightweight decision-support prototype that can be deployed with modest data to meet industry demand for scalable, low-cost analytics.

Future research will (i) test the framework across multiple 3DCP firms to assess external validity, (ii) integrate life-cycle-assessment data for a combined economic-environmental perspective, and (iii) connect the model to open-innovation platforms so that firms can share anonymised cost and performance datasets for increased generalisation, beyond the scope of a single case company and product.

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DATA AVAILABILITY STATEMENT

Some or all data, models, or code generated or used during the study are proprietary or confidential in nature.

REFERENCES

Akintoye, A. (2000). Analysis of factors influencing project cost estimating practice. Construction Management and Economics, 18(1), 77–89. https://doi.org/10.1080/014461900370979

Alam, A., Kozlova, M., Leifsson, L. T., & Yeomans, J. S. (2023). The Importance of Intelligent Colouring for Simulation Decomposition in Environmental Analysis. Journal of Environmental Informatics Letters, 10(2), 63-73.

Ayyagari, R., Chen, Q., & García de Soto, B. (2023). Quantifying the impact of concrete 3D printing on the construction supply chain. Automation in Construction, 155, Article 105032. https://doi.org/10.1016/j.autcon.2023.105032

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. Journal of Management, 17(1), 99-120. https://doi.org/10.1177/014920639101700108

Bertsimas, D., & Kallus, N. (2020). From Predictive to Prescriptive Analytics. Management Science, 66(3), 1025-1044. https://doi.org/10.1287/mnsc.2018.3253

Bischof, P., Mata-Falcón, J., & Kaufmann, W. (2022). Fostering innovative and sustainable mass-market construction using digital fabrication with concrete. Cement and Concrete Research, 161, 106948. DOI: 10.1016/j.cemconres.2022.106948

Bos, F., Wolfs, R., Ahmed, Z., & Salet, T. (2016). "Additive manufacturing of concrete in construction: potentials and challenges of 3D concrete printing." Architectural Engineering and Design Management, 12(6), 209-225. DOI: 10.1080/17452759.2016.1209867

Brealey, R. A., Myers, S. C., & Allen, F. (2011). Principles of Corporate Finance (10th ed.). McGraw-Hill/Irwin.

Cheng, T. C. E. (1991). An economic order quantity model with demand-dependent unit production cost and imperfect production processes. IIE Transactions, 23(1), 23-28. https://doi.org/10.1080/07408179108963838

Chopra, S., & Meindl, P. (2001). Supply Chain Management: Strategy, Planning, and Operation.

Curran, R., Raghunathan, S., & Price, M. (2004). Review of aerospace engineering cost modelling: The genetic causal approach. Progress in Aerospace Sciences, 40(8), 487–534. https://doi.org/10.1016/j.paerosci.2004.10.001

De Schutter, G., Lesage, K., Mechtcherine, V., Nerella, V. N., Habert, G., & Agusti-Juan, I. (2018). Vision of 3D printing with concrete — Technical, economic, and environmental potentials. Cement and Concrete Research, 112, 25-36. https://doi.org/10.1016/j.cemconres.2018.06.001

De Wolf, C., Pomponi, F., & Moncaster, A. (2017). "Measuring embodied carbon dioxide equivalent of buildings: A review and critique of current industry practice." Energy and Buildings, 140, 68-80. DOI: 10.1016/j.enbuild.2017.01.075

Dmitrenko, A., Lebedyk, G., & Nesterenko, M. (2018). Product Cost Calculation Methods in Construction. International Journal of Engineering & Technology, 7(3.2), 6-11.

Eastman, C., Teicholz, P., Sacks, R., & Liston, K. (2011). BIM handbook: A guide to building information modeling for owners, managers, designers, engineers, and contractors. John Wiley & Sons.

Eisenhardt, K. M. (1989). Building theories from case study research. Academy of Management Review, 14(4), 532-550.

Eisenhardt, K. M., & Graebner, M. E. (2007). Theory building from cases: Opportunities and challenges. Academy of Management Journal, 50(1), 25-32.

Eisenhardt, K. M., & Martin, J. A. (2000). "Dynamic capabilities: What are they?" Strategic Management Journal, 21(10-11), 1105-1121. DOI: 10.1002/1097-0266(200010/11)21:10/11<1105::AID-SMJ133>3.0.CO;2-E

Gardan J, Hedjazi L, Attajer A (2025). Additive manufacturing in construction: state of the art and emerging trends in civil engineering, ITcon Vol. 30, Special issue Construction 5.0, pg. 92-112, https://doi.org/10.36680/j.itcon.2025.005

Garrison, R. H., Noreen, E. W., & Brewer, P. C. (2021). Managerial accounting. McGraw-Hill.

Geissdoerfer, M., Morioka, S. N., de Carvalho, M. M., & Evans, S. (2018). Business models and supply chains for the circular economy. Journal of Cleaner Production, 190, 712-721. https://doi.org/10.1016/j.jclepro.2018.04.159

Gibb, A., & Isack, F. (2003). Re-engineering through pre-assembly: client expectations and drivers. Building Research & Information, 31(2), 146–160. https://doi.org/10.1080/09613210302000

Graser, K., Walzer, A. N., Hunhevicz, J. J., Jähne, R., Seiler, F., Wüst, R., & Hall, D. M. (2023). Qualitative technology evaluation of digital fabrication with concrete: Conceptual framework and scoreboard. Automation in Construction, 154, Article 104964. https://doi.org/10.1016/j.autcon.2023.104964

Hager, I., Golonka, A., & Putanowicz, R. (2016). "3D Printing of Buildings and Building Components as the Future of Sustainable Construction?" Procedia Engineering, 151, 292-299. DOI: 10.1016/j.proeng.2016.07.357

Hargadon, A., & Douglas, Y. (2001). When innovations meet institutions: Edison and the design of the electric light. Administrative Science Quarterly, 46(3), 476-501.

Hassan, H., Rodriguez-Ubinas, E., Al Tamimi, A., Trepci, E., Mansouri, A., & Almehairbi, K. (2024). Towards innovative and sustainable buildings: A comprehensive review of 3D printing in construction. Automation in Construction, 163, Article 105417. https://doi.org/10.1016/j.autcon.2024.105417

Horngren, C. T., Foster, G., Datar, S. M., Rajan, M., Ittner, C., & Baldwin, A. A. (2010). Cost accounting: A managerial emphasis. Issues in Accounting Education, 25(4), 789–790. https://doi.org/10.2308/iace.2010.25.4.789

Hubbard, D. W. (2020). The failure of risk management: Why it’s broken and how to fix it. John Wiley & Sons.

Hyperion. (2024). Hyperion Robotics homepage. Retrieved from https://www.hyperionrobotics.com/

Kozlova, M., & Yeomans, J. S. (2022). Monte Carlo enhancement via simulation decomposition: A “must-have” inclusion for many disciplines. INFORMS Transactions on Education, 22(3), 147-159.

Kozlova, M., & Yeomans, J. S. (2024). Sensitivity Analysis for Business, Technology, and Policymaking: Made Easy with Simulation Decomposition (SimDec). Taylor & Francis.

Kozlova, M., Ahola, A., Roy, P. T., & Yeomans, J. S. (2025). Simple binning algorithm and SimDec visualization for comprehensive sensitivity analysis of complex computational models. Journal of Environmental Informatics Letters, 13(1), 38-56. https://doi.org/10.3808/jeil.202400149

Kozlova, M., Collan, M., & Luukka, P. (2017). Simulation decomposition: New approach for better simulation analysis of multi-variable investment projects.

Kozlova, M., Lo Piano S., & Yeomans, J. S. (2024a). Methodological landscape of sensitivity analysis and the place of SimDec. In M. Kozlova & J. S. Yeomans (Eds.), Sensitivity Analysis for Business, Technology, and Policymaking Made Easy with Simulation Decomposition. Routledge.

Kozlova, M., Moss, R. J., Roy, P., Alam, A., & Yeomans, J. S. (2024b). SimDec algorithm and guidelines for its usage and interpretation. In M. Kozlova & J. S. Yeomans (Eds.), Sensitivity Analysis for Business, Technology, and Policymaking Made Easy with Simulation Decomposition. Routledge.

Kozlova, M., Moss, R. J., Yeomans, J. S., & Caers, J. (2024c). Uncovering heterogeneous effects in computational models for sustainable decision-making. Environmental Modelling & Software, 171, 105898.

Kucherenko, S., Klymenko, O. V., & Shah, N. (2017). Sobol' indices for problems defined in non-rectangular domains. Reliability Engineering and System Safety, 167, 218-231.

Le, T. T., Austin, S. A., Lim, S., Buswell, R. A., Law, R., Gibb, A. G. F., & Thorpe, T. (2012). Hardened properties of high-performance printing concrete. Cement and Concrete Research, 42(3), 558-566. https://doi.org/10.1016/j.cemconres.2011.12.003

Lim, S., Buswell, R. A., Le, T. T., Austin, S. A., Gibb, A. G., & Thorpe, T. (2012). "Developments in construction-scale additive manufacturing processes." Automation in Construction, 21, 262-268. DOI: 10.1016/j.autcon.2011.06.010

Mantha B R K, Kalasapudi V S, Upadhyaya A V A, Thomas A (2025). A life cycle cost analysis framework to compare fixed sensor network and on-demand robot-based data collection in indoor building environments, ITcon Vol. 30, pg. 1680-1706, https://doi.org/10.36680/j.itcon.2025.069

Marzban, S., & Lahmer, T. (2016). Conceptual implementation of the variance-based sensitivity analysis for the calculation of the first-order effects. Journal of Statistical Theory and Practice, 10, 589-611.

Mun, J. (2006). Real Options Analysis: Tools and Techniques for Valuing Strategic Investments and Decisions. John Wiley & Sons

Myers, D. (2003). The future of construction economics as an academic discipline. Construction Management and Economics, 21(2), 103–106. https://doi.org/10.1080/0144619032000056117

Myers, D. (2016). Construction Economics: A New Approach (4th ed.). Routledge. https://doi.org/10.4324/9781315645698

Nagatoishi, M. & Fruchter, R. (2023). Construction management in space: explore solution space of optimal schedule and cost estimate, ITcon Vol. 28, Special issue The future of construction in the context of digital transformation (CONVR 2022), pg. 597-621, https://doi.org/10.36680/j.itcon.2023.032

Needles, B. E., Powers, M., & Crosson, S. V. (2011). Principles of accounting. Cengage Learning.

Park, J., & Simpson, T. W. (2005). Development of a production cost estimation framework to support product family design. International Journal of Production Research, 43(4), 731–772. https://doi.org/10.1080/00207540512331311903

Pianosi, F., Beven, K., Freer, J., Hall, J. W., Rougier, J., Stephenson, D. B., & Wagener, T. (2016). Sensitivity analysis of environmental models: A systematic review with practical workflow. Environmental Modelling & Software, 79, 214-232.

Ranasinghe, M. (1996). Total project cost: a simplified model for decision makers. Construction Management and Economics, 14(6), 497–505. https://doi.org/10.1080/014461996373205

Robert, C. P., & Casella, G. (2004). Monte Carlo Statistical Methods. Springer New York. https://doi.org/10.1007/978-1-4757-4145-2

Roy, P. T., & Kozlova, M. (2024). Simulation Decomposition in Python. Journal of Open Source Software, 9(98), 6713.

Saltelli, A., Aleksankina, K., Becker, W., Fennell, P., Ferretti, F., Holst, N., ... & Wu, Q. (2019). Why so many published sensitivity analyses are false: A systematic review of sensitivity analysis practices. Environmental modelling & software, 114, 29-39.

Saltelli, A., Bammer, G., Bruno, I., Charters, E., Di Fiore, M., Didier, E., Nelson Espeland, W., Kay, J., Lo Piano, S., & Mayo, D. (2020). Five ways to ensure that models serve society: A manifesto. Nature, 582(7813), 482–484.

Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M., & Tarantola, S. (2008). Global sensitivity analysis: The primer. John Wiley & Sons.

Savage, S. L., & Markowitz, H. M. (2009). The flaw of averages: Why we underestimate risk in the face of uncertainty. John Wiley & Sons.

Siggelkow, N. (2007). Persuasion with case studies. Academy of Management Journal, 50(1), 20-24.

Tan, T., Graser, K., Walzer, A. N., Ng, M. S., & Hall, D. M. (2025). Exploring the implementation of digital fabrication in construction: Combining system approaches and a revelatory case study from Switzerland. Journal of Construction Engineering and Management, 151(12), 05025016. https://doi.org/10.1061/JCEMD4.COENG-16680

Tan, T., Mills, G., Papadonikolaki, E., & Liu, Z. (2021). Combining multi-criteria decision making (MCDM) methods with building information modelling (BIM): A review. Automation in Construction, 121, 103451. https://doi.org/10.1016/j.autcon.2020.103451

Taylor, J. E., Dossick, C. S., & Garvin, M. (2010). Meeting the burden of proof with case-study research. Journal of Construction Engineering and Management, 137(4), 303-311. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000283

Taylor, J., & Levitt, R. (2004). Understanding and managing systemic innovation in project-based industries. Innovations: Project Management Research, 2004, 83-99. Project Management Institute.

Teece, D. J., Pisano, G., & Shuen, A. (1997). "Dynamic capabilities and strategic management." Strategic Management Journal, 18(7), 509-533. DOI: 10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z

Trigeorgis, L. (1996). Real Options: Managerial Flexibility and Strategy in Resource Allocation. MIT Press.

Trigeorgis, L., & Reuer, J. J. (2017). Real options theory in strategic management. Strategic Management Journal, 38(1), 42–63. https://doi.org/10.1002/smj.2593

Walzer, A. N. (2025). Assessing multi-level uncertainties in construction robotics entrepreneurship by means of methodological pluralism (Doctoral dissertation). ETH Zurich. https://doi.org/10.3929/ethz-b-000705101

Walzer A. N., Kozlova, M., & Yeomans, J. S. (2024). Printing homes: Unit cost estimation for additive manufacturing in construction. In M. Kozlova & J. S. Yeomans (Eds.), Sensitivity Analysis for Business, Technology, and Policymaking Made Easy with Simulation Decomposition. Routledge. https://doi.org/10.4324/9781003453789-8

Walzer, A.N., Kozlova, M., Mohite A., and Yeomans, J.S. (2024a). “Improving a 3D Concrete Printing Factory Using Stochastic Modelling for Decision-Support”. In: 4th RILEM International Conference on Concrete and Digital Fabrication, Munich, Germany, September 04-06, 2024. https://doi.org/10.3929/ethz-b-000692647

Walzer, A. N., Tan, T., Graser, K., & Hall, D. M. (2024b). Bug or feature? Institutional misalignments between construction technology and venture capital. Construction Management and Economics, 43(2), 130–152. https://doi.org/10.1080/01446193.2024.2401818

Wernerfelt, B. (1984). A resource-based view of the firm. Strategic Management Journal, 5(2), 171-180. https://doi.org/10.1002/smj.4250050207

Wu, S., Walzer, A. N., Kahlert, A., Dillenburger, B., & Hall, D. M. (2024). Understanding stakeholders' intention to use construction robots: A fuzzy-set qualitative comparative analysis. Construction Robotics, 8(5), Article 5. https://doi.org/10.1007/s41693-024-00115-z

Yin, R. K. (2018). Case Study Research and Applications: Design and Methods. Sage publications.