Universal Library of Innovative Research and Studies | Research Article

ISSN: 3065-0003 | Volume 2, Issue 3

Open Access | PP: 88-93

DOI: https://doi.org/10.70315/uloap.ulirs.2025.0203016

Optimization of Project Cost Estimation Processes in Precision Manufacturing

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Abstract

The article is dedicated to the optimization of project cost estimation processes in precision manufacturing as an operational problem emerging at the quotation stage. Relevance follows from the growing mismatch between complex production conditions and simplified estimation practices, where geometric variability and process dependencies reduce pricing reliability. The novelty is associated with the interpretation of cost estimation as a layered analytical system embedded in RFQ workflows rather than a terminal calculation procedure. The work describes how technical information is transformed into operational parameters and subsequently into cost structures through interacting process layers. Special attention is paid to manufacturability interpretation, temporal redistribution of operations, and sensitivity of cost drivers under variable production conditions. The work sets itself a task to explain the internal mechanisms that determine estimation accuracy and pricing stability. Analytical comparison and conceptual interpretation of recent studies are used to identify structural relationships between estimation models and production processes. The conclusion describes a shift toward adaptive and process-integrated estimation systems. The article will be useful for engineers and manufacturing decision-makers.

Keywords: *Precision Manufacturing, Cost Estimation, Manufacturability, Process Modeling, Production Systems.*

INTRODUCTION

Precision manufacturing systems increasingly reveal a divergence between how production actually unfolds and how its cost is estimated at the quotation stage. Complex geometries, multi-stage processing, and variable resource conditions disrupt stable relationships between inputs and outputs. Cost does not follow a fixed trajectory. It emerges through interactions. When these interactions are not interpreted, estimation becomes approximate and pricing loses structural grounding.

Within RFQ workflows, estimation systems are required to interpret incomplete technical information and translate it into operational parameters. Drawings define geometry, but they also imply constraints: tool accessibility, machining orientation, sequence of operations. These constraints reshape time structures and resource allocation. Estimation begins to depend on how accurately these implications are detected. Weak interpretation leads to early misalignment. It accumulates.

The aim of the study is to theoretically substantiate and develop a process-integrated model of cost estimation that reflects the interaction between engineering interpretation, process sequencing, and economic evaluation in precision manufacturing.

Three research objectives follow from this formulation. The first is to capture how technical parameters are transformed into process and cost structures within estimation systems. The second is to detect how manufacturability constraints and process configuration reshape time distribution and resource usage. The third is to interpret how the integration of process-based and data-driven approaches alters estimation behavior and decision-making during quotation.

The hypothesis assumes that estimation accuracy and pricing stability improve when cost formation is modeled as a system of interacting operational layers, which can be identified, structured, and analytically interpreted within the estimation process.

The novelty arises from addressing the insufficient explanation of how engineering interpretation, process sequencing, and economic evaluation interact within estimation systems, and from presenting these elements as a continuous analytical mechanism rather than separate stages.

METHODS AND MATERIALS

The literature base was assembled through targeted retrieval from international scientific databases, including Scopus, Web of Science, and IEEE Xplore, with emphasis on publications from the last five years. Search logic combined keyword

Citation: Iryna Honcharuk, "Optimization of Project Cost Estimation Processes in Precision Manufacturing", Universal Library of Innovative Research and Studies, 2025; 2(3): 88-93. DOI: https://doi.org/10.70315/uloap.ulirs.2025.0203016.

clusters such as "cost estimation AND manufacturing," "process modeling OR production systems," and "machine learning AND cost prediction," allowing identification of studies where cost formation is linked to process behavior.

Approximately 40 sources were initially identified and reduced to 12 through selection based on analytical depth and the presence of explicit relationships between technical parameters, operational processes, and cost structures. Preference was given to studies describing implementation detail and interaction between system elements rather than isolated performance indicators.

The reviewed studies reflect a range of heterogeneous analytical orientations, where process-oriented models depict the interaction between machining duration, setup procedures and auxiliary operations within production flows, activity-focused approaches break down costs across operational phases and expose uneven patterns of resource allocation, data-driven frameworks interpret cost structures through pattern recognition across datasets with adaptive forecasting, while simulation-based investigations replicate fluctuations in time and resource usage, thereby uncovering dependencies that remain obscured in static representations.

Despite this variation, a shared limitation becomes apparent, since these methods describe isolated elements of estimation systems yet rarely clarify their interconnection, as process sequencing is examined without accounting for variability, predictive frameworks function without transparent structural explanation, and cost decomposition remains detached from the dynamic behavior of processes. The interaction between these elements remains insufficiently clarified.

This observation leads to the reinterpretation of cost estimation as an internally connected system in which engineering interpretation, temporal structuring, and economic evaluation operate simultaneously. The present study follows this direction.

RESULTS

Cost estimation in precision manufacturing does not behave as a final calculation stage. It operates as an embedded analytical layer inside the quotation process, where technical interpretation, resource projection, and economic evaluation unfold simultaneously. At the RFQ stage, estimation systems are forced to reconstruct the future production scenario from incomplete inputs—drawings, tolerances, material specifications—and translate them into structured cost signals. The accuracy of this translation depends less on historical averages and more on how precisely the system interprets manufacturability constraints. When this interpretation is weak, pricing becomes detached from production reality. Misalignment emerges early.

A consistent pattern appears when estimation is treated as a sequence of interacting operational layers rather than a single model. Technical geometry initiates the chain. It defines machining accessibility, tool selection, and process routing. These parameters immediately reshape time structures—setup duration, cycle time, auxiliary operations—which in turn determine labor and machine load. Cost is not assigned afterward. It forms within this chain. This is why estimation frameworks that integrate engineering analysis at the quotation stage produce more stable pricing behavior (Table 1). They do not approximate cost. They reconstruct it from process conditions.

Table 1. Structural decomposition of cost estimation components in precision manufacturing systems (compiled by the author based on Shamim et al., 2025; Neamah et al., 2024; Liu and Cheng, 2024)

Estimation Layer	Functional Role	Input Parameters	Transformation Mechanism	Output Effect
Geometry Analysis	Defines manufacturability	CAD models, tolerances	Feature interpretation	Process feasibility
Process Planning	Determines routing	Machine capabilities, tooling	Operation sequencing	Time structure
Resource Allocation	Assigns resources	Labor, material, equipment	Load distribution	Cost drivers
Time Modeling	Structures duration	Setup, cycle time	Temporal redistribution	Unit cost variation
Risk Evaluation	Identifies uncertainty	Constraints, variability	Scenario adjustment	Pricing stability

Artificial intelligence-based estimation systems intensify this mechanism by shifting the source of prediction from predefined relationships to data-driven pattern recognition. Predictive accuracy reaches 85–90% in complex environments when deep learning models are applied, while traditional regression structures remain within 70–80% due to linear assumptions that fail under variable process conditions (Shamim et al., 2025). The difference is not purely numerical. It reflects a structural change in how cost drivers are interpreted. Machine learning models absorb nonlinear dependencies between geometry, labor variability, and material dynamics. Estimation becomes adaptive. Static quoting loses relevance.

At the same time, the internal decomposition of manufacturing cost reveals that estimation accuracy depends on how process stages are segmented and evaluated. When production is structured into pre-processing, processing, and post-processing, cost distribution becomes highly uneven. In a validated production scenario, processing accounts for 57% of total cost, pre-processing for 38%, and post-processing for only 5% (Neamah et al., 2024). This imbalance reflects the concentration of resource consumption during active material transformation. It also exposes where estimation errors are most likely to occur. Underestimation rarely originates in finishing operations. It accumulates in machining time and setup assumptions.

The internal composition of cost drivers reinforces this observation. Labor contributes 56% of total cost, while material accounts for 21%, with machine, overhead, and energy forming smaller but structurally linked components (Neamah et al., 2024). The system reacts strongly to labor variability. A 40% increase in operator cost produces a 43.2% increase in total cost, while the same variation in machine maintenance results in only a 1.6% change (Neamah et al., 2024). Sensitivity is not evenly distributed. It concentrates in human-controlled operations (Figure 1). Estimation models that fail to isolate these sensitivities produce unstable pricing.

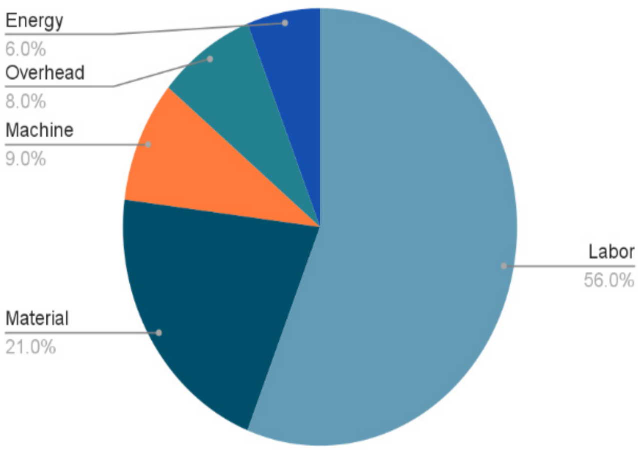

Figure 1. Distribution of cost components in precision manufacturing systems (compiled by the author based on Neamah et al., 2024; Reis et al., 2025; Liu and Cheng, 2024)

Time behaves as a controlling variable rather than a neutral parameter. Its structure determines how cost is distributed across units. When production volume increases within a single manufacturing cycle, fixed-time operations—setup, calibration, system preparation—are redistributed across multiple parts. This changes the cost architecture. In a representative case, increasing the number of parts from 1 to 100 reduced processing time per part from 11.7 hours to 15 minutes, while total production time increased only from 11.7 hours to 24.3 hours (Karaş and Shokrani, 2025). The implication is direct. Unit cost does not scale linearly with production time. It collapses when fixed operations are shared.

The same mechanism governs cost reduction. Packing multiple components into a single build reduces unit cost by up to 98%, decreasing from £640.23 to £15.07 due to the redistribution of setup and machine usage across the batch (Karaş and Shokrani, 2025). Efficiency emerges from structural sharing, not acceleration. Yet this effect is conditional. When geometric constraints limit build capacity, cost concentration shifts back to the processing stage. In large-volume components, build-related activities account for 75.5% of total cost, dominated by material consumption, energy use, and machine time (Karaş and Shokrani, 2025). In such cases, optimization through volume scaling becomes impossible. Estimation must recognize these constraints before quotation is finalized.

Manufacturability analysis becomes the pivot of the estimation system at this point. Geometry does not only define shape. It determines feasible production routes, build orientation, support structures, and post-processing requirements. These parameters alter both time and cost simultaneously. Support structures alone can increase cost due to extended build time and additional removal operations, even when their material contribution appears minor (Karaş and Shokrani, 2025) (Figure 2). Estimation systems that exclude manufacturability from early analysis systematically underestimate complexity. The error propagates into pricing.

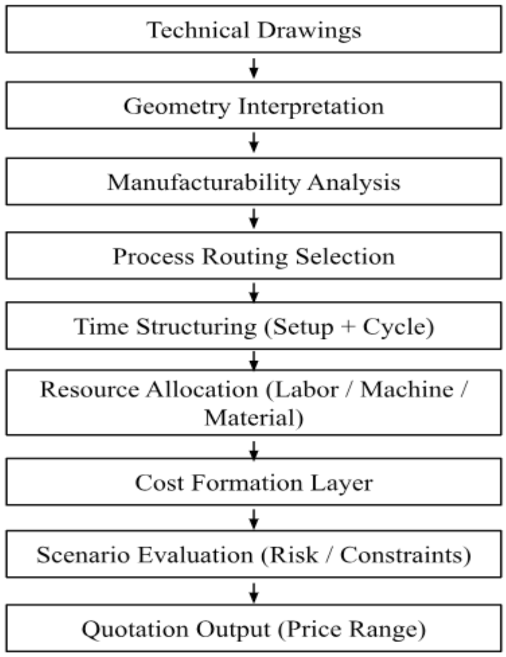

Figure 2. Scheme of integrated cost estimation workflow at RFQ stage in precision manufacturing (compiled by the author based on Karaş and Shokrani, 2025; Fahad et al., 2025; Hegazi, 2024)

Process-based estimation models attempt to stabilize this behavior by embedding cost calculation within the sequence of manufacturing operations. Instead of aggregating resources, these models track how each operation consumes time, labor, and equipment capacity (Liu and Cheng, 2024). The estimation becomes conditional on process flow. Machining time, setup configuration, and auxiliary operations are evaluated as interdependent variables rather than independent inputs. This approach aligns estimation with production logic. It reduces abstraction.

Dynamic modeling extends this structure further by introducing variability into estimation. Discrete-event simulation captures fluctuations in processing time, machine utilization, and workflow interruptions, allowing cost structures to be evaluated under changing production conditions (Karaş and Shokrani, 2025). This uncovers latent cost drivers, especially within post-processing stages, where inspection procedures, finishing activities and corrective actions generate variability that remains unaccounted for in static models. Estimation becomes scenario-based. It anticipates deviation rather than assuming stability.

Economic feasibility introduces another layer into estimation logic. Additive manufacturing demonstrates cost advantages in low to medium production volumes, where the absence of tooling reduces fixed costs. At higher volumes, conventional manufacturing regains efficiency due to cost amortization across larger batches (Zinzombe et al., 2025). Estimation systems must therefore incorporate volume thresholds as decision variables. The quotation process implicitly becomes a selection mechanism between alternative manufacturing routes. Cost is evaluated together with feasibility.

Artificial intelligence-based estimation systems reinforce this decision-oriented structure by integrating cost prediction with adaptive data flows. These systems process real-time inputs—material prices, labor availability, machine load—and continuously update cost projections, allowing dynamic adjustment during quotation (Hegazi, 2024; Ning et al., 2020). The estimation output is no longer a single value. It becomes a range of scenarios. Each scenario reflects a different configuration of constraints. Decision-making shifts toward risk management.

Quality-related factors introduce additional complexity into cost estimation. Inspection strategies and defect probabilities influence both cost and time structures. When integrated into digital manufacturing environments, quality data allows estimation systems to predict inspection costs and potential rework before production begins (Reis et al., 2025). Cost estimation expands beyond resource calculation. It begins to capture uncertainty.

Several limitations remain visible. Many models rely on datasets tied to specific production environments, limiting their transferability. Variability in equipment, materials, and workforce conditions reduces consistency across applications. High computational requirements restrict real-time implementation in some settings. Model interpretability remains constrained, particularly in deep learning systems where prediction logic is not easily accessible. These constraints do not invalidate the models. They define their operational boundaries.

The estimation process changes its nature under these conditions. It no longer functions as a supporting calculation within project planning. It becomes an operational system embedded in quotation, linking engineering interpretation, process simulation, and economic evaluation into a continuous analytical cycle. Pricing decisions emerge from this cycle.

DISCUSSION

The estimation process in precision manufacturing reveals a structural tension between engineering interpretation and economic formalization that becomes particularly visible at the quotation stage. Cost does not emerge as a direct numerical output of predefined formulas. It is constructed through successive transformations of technical information into operational parameters and then into resource allocations. Within this chain, even minor misinterpretations of geometry or process constraints propagate into measurable deviations in pricing. The system behaves as an inference mechanism rather than a calculator. It interprets before it computes.

A recurring observation concerns the instability of traditional estimation approaches when confronted with high variability in manufacturing conditions. Conventional models tend to rely on averaged historical data or simplified parametric relationships, which assume stable correlations between inputs and outputs. In practice, these correlations weaken under conditions of complex geometry, multi-stage processing, and fluctuating resource availability. Cost drivers interact in non-linear ways. Machine time depends on tool accessibility, which depends on geometry, which in turn reshapes setup configuration. The system becomes recursive. Earlier studies already pointed to these limitations, particularly in environments where manual estimation and expert judgment dominate. The present analysis reinforces this view but clarifies the mechanism: instability originates not from data scarcity, but from insufficient representation of process interdependencies.

The introduction of structured evaluation frameworks changes the internal logic of estimation by reorganizing how information flows between stages. Instead of aggregating cost components at the end of analysis, structured approaches begin with manufacturability interpretation. Technical drawings are not treated as static inputs. They are decomposed into operational implications—machining sequences, support requirements, surface finishing constraints. Each implication modifies time allocation and resource consumption. The estimation process becomes layered. Engineering analysis feeds directly into cost formation. Earlier work on activity-based costing anticipated this transition by linking costs to specific operations, yet often remained static in its treatment of process dynamics. What becomes evident here is that segmentation alone is insufficient unless it is coupled with continuous interaction between layers.

A similar shift can be observed in process-based models, where cost estimation is embedded within the production workflow itself. These models do not assign cost after defining the process. They define cost through the process. Machining time, setup duration, and auxiliary operations are evaluated as mutually dependent variables, forming a network rather than a sequence. Under such conditions, estimation precision improves not due to increasing model complexity but as a result of closer alignment with actual production progression, while earlier investigations emphasized the identification of cost drivers—labor, material usage and machine utilization—the present analysis advances this perspective by demonstrating that their influence acquires a conditional character, since their weight shifts depending on process configuration and integration.

Time assumes a leading organizational role within this system, functioning not merely as a duration metric but as a mechanism that redistributes cost across operational layers, where an increase in production volume within a single manufacturing cycle leads to the sharing of time-dependent activities such as setup and calibration across multiple units, thereby diminishing their contribution to unit cost, as prior research in additive manufacturing highlighted this effect in relation to build volume utilization, whereas the current findings refine this interpretation by indicating that cost reduction arises not from accelerated production but from temporal reallocation, in which fixed operations lose dominance when distributed while variable operations persist.

This observation prompts a more profound reconsideration of production scalability, since cost estimation systems implicitly embed the assumption that higher volume enhances efficiency, yet in precision manufacturing this principle holds only under specific geometric and technological conditions, as when component dimensions exceed build capacity or require individualized processing cost concentration shifts back toward resource-intensive stages such as machining and material transformation, and although previous studies identified the economic advantage of additive manufacturing within low to medium production volumes, the underlying mechanism becomes more explicit through the estimation system perspective, where scalability appears constrained not solely by economic factors but by process architecture.

Artificial intelligence-based estimation systems further modify this architecture by introducing adaptive data processing into the estimation workflow. These systems do not operate on fixed relationships between variables. They detect patterns across large datasets and continuously update predictions as new data becomes available. Earlier research demonstrated the superior accuracy of such models, particularly in environments characterized by high variability. The current discussion suggests that their advantage lies in how they restructure the estimation process. Instead of producing a single deterministic estimate, they generate a range of possible outcomes based on different input configurations. Estimation becomes probabilistic. Decision-making shifts toward evaluating uncertainty.

At the same time, the integration of real-time data streams introduces a new form of dependency. Estimation accuracy becomes linked to data availability and quality. Material prices, labor rates, and machine performance must be continuously updated for the system to function effectively. Previous studies emphasized the potential of AI to incorporate such variables into cost prediction. What remains less explored is the operational implication: estimation systems become part of a broader digital infrastructure. They rely on data flows that extend beyond the production environment. Interruptions in these flows reduce predictive reliability. The system weakens.

Quality-related factors introduce additional complexity into cost estimation. Inspection requirements, defect probabilities, and rework operations influence both cost and time structures. Earlier work on manufacturing systems highlighted the relationship between quality control and production cost, particularly in digital environments. The present analysis suggests that quality should be treated as an embedded cost driver rather than an external correction mechanism. When inspection strategies are integrated into estimation models, potential deviations are identified earlier. Cost estimation expands to include risk anticipation. The system becomes more preventive.

Despite these advancements, several limitations should be acknowledged. The analysis relies on previously published studies, many of which are based on specific industries such as additive manufacturing, construction, or healthcare. Differences in methodological design restrict direct comparison across these domains. Variations within datasets, especially regarding scale and regional specificity, constrain the broader applicability of the results. Many models are validated under controlled conditions and lack extensive real-world implementation. Computational complexity presents another constraint, especially for AI-based systems requiring large datasets and processing capacity. Interpretability remains an unresolved issue. Complex models produce accurate predictions, but their internal logic is not always transparent to practitioners.

Another limitation concerns the representation of manufacturability within estimation systems. While process-based models capture operational sequences, they do not always fully account for technological constraints such as tool accessibility, machine limitations, or operator skill variability. These factors influence cost formation but are difficult to formalize within existing models. As a result, estimation accuracy may still depend on implicit expert knowledge. The system remains partially opaque.

The discussion of previous research reveals a gradual convergence toward integrated estimation frameworks, yet this convergence remains incomplete. Activity-based costing introduced process segmentation but often lacked dynamic adaptability. Process-based models improved structural alignment with production but remained sensitive to input assumptions. AI-based approaches increased predictive accuracy but introduced dependency on data infrastructure and raised concerns regarding interpretability. Each approach addresses a specific limitation while introducing new constraints. The estimation system evolves through accumulation rather than replacement.

What emerges from this analysis is not a unified model of cost estimation, but a transformation in how estimation is positioned within manufacturing systems. It no longer functions as a discrete stage preceding production. It operates as a continuous analytical layer embedded within quotation, planning, and execution. Engineering interpretation, process simulation, and economic evaluation converge within this layer. The boundaries between them become less distinct.

CONCLUSION

The analysis clarifies how cost estimation in precision manufacturing is formed through interacting operational layers rather than isolated calculations. The first objective is addressed by showing that technical parameters are transformed into cost structures through successive interpretation of geometry, process configuration, and resource allocation. The second objective is resolved by demonstrating that manufacturability constraints and temporal redistribution directly reshape cost behavior and determine sensitivity to labor and process conditions. The third objective is fulfilled through the interpretation of integrated estimation approaches, where process-based, simulation, and data-driven models contribute to a more adaptive estimation structure.

The hypothesis is supported by the observed shift from static cost assignment toward dynamic reconstruction of cost within the estimation process. The study contributes to the theoretical development of cost estimation by conceptualizing it as a process-integrated system rather than a discrete calculation procedure. From a practical perspective, the results can be applied to improve RFQ processes, reduce pricing deviations, and enhance decision-making in precision manufacturing environments.

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