A Unified Cost Estimation Framework Combining Milling, Turning, AM, and Sheet Metal Processing

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Abstract. Rapid and reliable cost estimation is a key enabler during early design phases and make-or-buy decisions, while associated design variants are managed within Product Lifecycle Management (PLM) systems. Service providers for prototype parts and small production series have emerged; however, their offerings are typically restricted to a limited set of manufacturing technologies. This paper presents a transparent, process-based instant quoting approach that integrates multiple manufacturing technologies within a unified system. The proposed system follows a process-based Product Cost Estimation methodology grounded in Time-Driven Activity-Based Costing (TDABC). Manufacturing costs are derived from automatically generated manufacturing steps based on feature recognition, yielding objective machine time estimates for different manufacturing processes and technology-specific auxiliary operations. A modular system architecture currently supports milling, turning, polymer and metal additive manufacturing (AM), and sheet metal cutting and bending, and is designed for straightforward extensibility. A central contribution of this work addresses the persistent challenge of incomplete product manufacturing information (PMI) in CAD exchange formats, which is further compounded by the limited adoption of PMI in contract manufacturing. To preserve cost-relevant design intent, an artificial intelligence (AI) component interprets tolerances and surface specifications from 2D drawings and associates them with corresponding 3D geometry elements. First validation steps against manually generated quotations demonstrates good agreement across different manufacturing technologies. The platform delivers quotations within one minute and provides a basis for continuous improvement through feedback from real production data, thereby supporting Design for Manufacturing (DfM) and informed decision-making.

Keywords: Cost Estimation, Instant Quoting, Product Manufacturing Information, Multi-Process Manufacturing.

1 Introduction and Goal

The increasing demand for customised components in both prototyping and small-series production leads to an increase in commercially available service providers with their digital platforms (instant quoting systems). Traditional solutions often focus on single-process capabilities, such as milling or turning, which limits flexibility and efficiency when complex parts require multiple technologies (see Chapter 2.2). This research project was initiated to address these limitations by developing a commercial platform capable of supporting a broader spectrum of manufacturing processes within a unified service environment. The business covers prototype parts and turns this leads into orders and long-term relationships for serial parts for recurring revenues.

The initial foundation of the platform provided functionality for milling and turning operations. However, to meet contemporary industrial requirements, this basis had to be extended, while the automated recognition algorithms to identify the appropriate manufacturing technology for each component had to be improved. The extension of the platform had to incorporate additive manufacturing in plastics and metals. Additionally, sheet metal processing capabilities (cutting and bending) were to be integrated to enable comprehensive production workflows.

A critical aspect of the project was improving the accuracy of cost estimation, which is essential for both customers and service providers. Key Performance Indicators (KPIs, see Chapter 4, page 7) have been defined, guiding the development of cost models and validation processes being capable to reduce safety margins and to offer better prices. The platform architecture must have a modular design, to ensure scalability and enabling the combination of different manufacturing technologies within a single order (see Chapter 3.1). This approach not only supports complex component requirements but also facilitates future technological integration.

The project successfully met its technical objectives, and the part quotation is offered within less than one minute. Nevertheless, the planned commercial launch was postponed due to strategic business considerations. Instead, the platform is being transferred to the ZHAW Zurich University of Applied Sciences for internal use, where ongoing research focuses on refining cost estimation methodologies and further enhancing system capabilities. This paper summarises a project while detail research and development are published individually: [1–7]

2 Methods and Available Services

2.1 Cost Calculation Methods

Two alternative cost-calculation approaches were in a first step evaluated in a controlled test environment, systematically compared, and analysed to determine the most suitable method for operational deployment (see Chapter 2.2).

- Methods applying algorithms based on part features (“feature-based”) and associated feature-specific cost elements (“process-based”) [8, 9].
- Methods employing machine-learning techniques that derive cost analogies (“analogy”) by comparing new components with existing reference parts [10] or via statistics (“parametric”).

Simulations, including virtually replicating the full manufacturing process, for high-fidelity cost data has not been considered. It is more rooted in a proper CAD-CAM process and would not fulfil the requirement regarding cost calculation velocity ("offer within a minute").

2.2 Available Services and Software

A variety of tools are commercially available while the provided services are split into two segments – (A) offering part manufacturing services and (B) cost estimations on-premise [7], typically specialised for a particular manufacturing technology (e.g. Blexon for sheet metal working). As well for Additive Manufacturing (AM) related services are available [3].

- (A) **Services.** E.g. Xometry, Protolabs, InstaWerk, and Blexon [11–14]
- (B) **Cost Estimation Tool.**
  - Feature-based: E.g. TICC, 3D Spark, aPriori, and Classmate [15–18]
  - Machine learning: E.g. Cost It Right, Shouldcosting [19, 20]

As only one tool is preferable for the system (see **Fig. 1**, page 4), TICC has been selected, knowing that gaps regarding additive manufacturing and sheet metal work have to be closed. The present situation for milling and turning required an optimisation (technology recognition and cost estimation).

Based on the evaluation results, the decision was made to implement the feature-based approach, specifically TICC by R+B [15], rather than the machine-learning-based method tested via Shouldcosting [20]. The decisive advantages of the selected approach include:

- Machine-learning models require extensive datasets linking estimated and actual costs, which are unavailable because suppliers provide the components and thus no continuous learning cycles can be established.
- The feature-based method enables the integration of new manufacturing technologies, such as additive manufacturing, without the need for long-term model training.
- The selected tool TICC allows the direct use of the additively manufactured raw part as input for final machining, thereby supporting the Formal Quality Level (FQL) approach for cost estimation. This results in enhanced competitiveness through adaptable safety margins (see Chapter 4, page 7).
- The automated identification of the appropriate manufacturing technology improves the customer experience and streamlines the ordering process.

3 System Setup and Challenges

3.1 Cloud-Based System Setup

The selected approach is process-based (see Chapter 2.2) and follows Time-Driven Activity-Based Costing (TDABC [21]), with mainly the estimated time (mostly machine time) required to perform activities, as well as a capacity cost rate. In this work, the primary and most objective time driver is derived from an automatically generated manufacturing steps, based on part features and similar to CAM (Computer-Aided Manufacturing). It provides cutting time as well as automatically implied machine-time elements (e.g., tool changes and other program-driven non-cutting contributions). Other technology-specific auxiliary tasks are treated pragmatically using manufacturer experience, individually set upon each manufacturing technology.

The system (**Fig. 1**) is deployed in a Microsoft Azure cloud environment. Its core component is a virtual machine running the TICC software by R&B. TICC is a software solution for the universal generation of CAM programs. For this application, its automation capabilities were adapted and extended. Surrounding this core is an automation framework that includes, among other components, a web interface through which data can be uploaded, configured, and ultimately priced. The system also has access to CRM data in order to associate customers and orders. Communication is handled via Azure Service Bus, which also triggers the cost calculation process. Key elements to be considered:

- Existing platforms are proprietary and therefore non-transparent to customers. The internal functionalities are treated as a kind of business secret.
- Highly mature platforms do exist, but they are typically limited to a single manufacturing technology. This development integrates multiple manufacturing technologies into a unified framework.
- Existing platforms each exhibit specific strengths and weaknesses. None of these platforms currently use 3D annotations or tolerances and surface finish requirements extracted from 2D drawings, both of which are addressed by the solution presented in this paper (see Chapter 3.2).

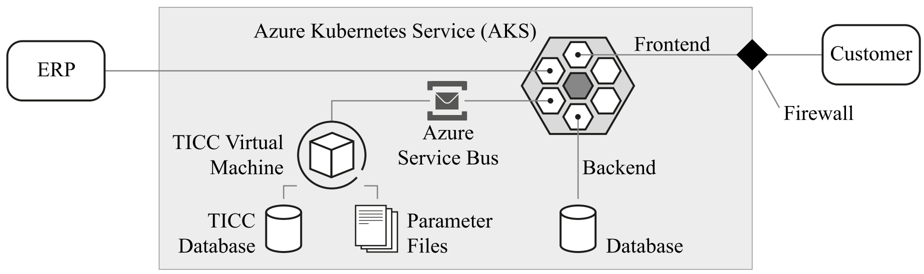

Fig. 1. System overview

3.2 An Applied AI Approach to Extract and Reintegrate Tolerances

Classic Method and 3D-Master Approach. Transferring tolerances to an instant quoting system represents a significant challenge. Traditionally, mechanical engineering relies on a 2D technical drawing that is transmitted together with the 3D data, usually as a neutral STEP file. Geometric tolerances, surface qualities, and additional requirements are annotated on the drawing. The manufacturer interprets the drawing and adapts the manufacturing strategy based on experience to meet the specified tolerances.

Often, simple measurement tools are used to verify critical features, and manufacturing programs are adjusted or refined accordingly.

A more recent method is the 3D-Master approach. All tolerances are defined directly in the 3D model, and no separate drawing is derived. From these 3D models with annotations a 3D PDF can be generated, allowing a viewer without specialised software to rotate the part interactively and to inspect predefined 2D views containing the corresponding tolerances. A 3D PDF has several drawbacks, including no machine readability. As a viable alternative, the STEP format also supports such 3D annotations and enables the geometry to remain machine-readable. Beyond interoperability, STEP with embedded product manufacturing information (PMI) also offers a practical advantage in terms of cybersecurity. Interactive 3D PDFs typically require JavaScript to be enabled in the viewer, which constitutes a well-known attack vector, a concern particularly acute for contract manufacturers who routinely receive files from a wide range of external customers. STEP, as a pure data format, eliminates this class of risk entirely.

Incomplete STEP Exports as a Challenge. While modern CAD programs can add PMI, they lack the ability to export the model and PMI in a complete form into STEP or alternative formats (e.g. IGES, OWL, or STL), even though the STEP standard (AP 242 3rd edition) would enable it [6]. Therefore, the gap of insufficient manufacturing information adds uncertainties to the cost calculation tools. For example, considering material information or general tolerance information (ISO 2768) is today not possible with a STEP file including PMI.

One countermeasure is to apply a safety margin while calculating the price. However, more promising is applying AI to interpret the optionally uploaded drawings. This additional information can be fed directly to the cost calculation tool or be reintegrated first within the uploaded STEP file (e.g. EasySTEP [22], a conceptual model and toolset for non-geometric data like PMI, materials, requirements in STEP files across the product lifecycle).

AI as a Solution to Information Extraction from Drawings. To bridge the gap between the still widely used 2D drawings and the currently incomplete implementation of 3D tolerancing in the 3D-Master approach, the proposed solution employs artificial intelligence to extract tolerances (or, more precisely, geometric dimensioning & tolerancing information, GD&T) from 2D drawings. The methodology addresses a fundamental limitation in automated drawing interpretation, representing a key development and major novelty of the framework [2].

Conventional computer vision methods, such as object detection or semantic segmentation, treat document recognition as a task of extracting isolated, partial descriptions [23]. However, when holistic analysis is required for documents whose interpretation is bound to established conventions (e.g., engineering drawings), this approach is inherently insufficient because it ignores the essential semantic relationships between the extracted symbols. For example, simply detecting a tolerance value or a dimension annotation provides little value if its relationship to a specific geometric facet is missing.

To overcome this limitation, the document recognition has been reframed to a complete document-to-record transcription task rather than a conventional vision problem for partial information extraction, arguing that convention-bound documents encode exact information that must be fully recovered, not merely partially detected. This perspective reveals that documents naturally group according to their intrinsic information structures, guiding the design of the underlying learning systems. By introducing a structure-specific inductive bias, the world's first end-to-end model, capable of fully transcribing simplified engineering drawings, has been trained. The underlying system utilises a transformer-based encoder-decoder architecture with a non-sequential, graph-based prediction bias that is specifically designed to first predict the set of visible elements (record nodes) and subsequently infer their exact connections (relationship nodes). Because this AI model extracts a complete, interlinked record rather than detecting isolated primitives, the resulting output provides exactly the structured semantic data required by automated downstream tasks.

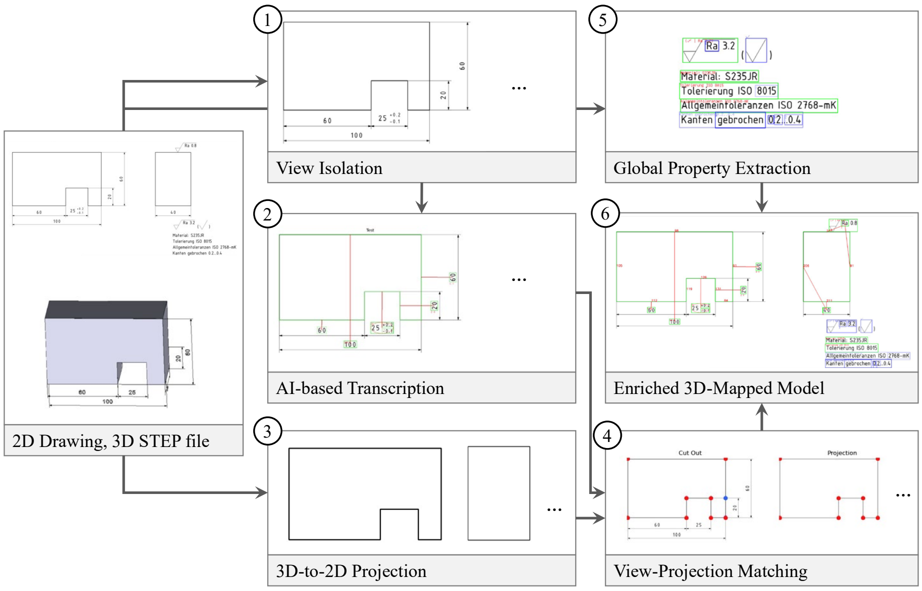

Fig. 2. Pipeline for enriching 3D STEP models with PMI extracted from 2D drawings

As illustrated in **Fig. 2**., mapping the AI-generated 2D understanding back to the 3D STEP domain requires a multi-step pipeline, in which the AI system described in [2] processes to extract geometry, tolerancing elements, and their relations (2). To translate this 2D understanding to the 3D domain, the 3D STEP file is projected using the hidden-line-removal algorithm [24] into various 2D orientations (3). These projections are then heuristically matched pairwise with their corresponding 2D views (4). During projection, the originating 3D edge identifier is stored for each 2D element, effectively forming a bridge between the 2D and 3D domains. Concurrently, global drawing information (e.g., material specifications, general ISO tolerances) is acquired through symbol spotting and text extraction (5). The extracted text is parsed via heuristic rules to categorise it into explicit properties, e.g., the material. Ultimately, this process yields a fully enriched, 3D-mapped model by combining the mapping between 2D edges and 3D edges with the extracted relationships between 2D edges and tolerances (6). This way, a list of features with critical tolerances mapped to 3D primitives is generated. These features are considered within the TICC software by applying additional measures, such as extra finishing passes or the use of additional tools.

When the 3D-Master approach is used, tolerances are extracted directly by the underlying STEP interpreter.

4 The Different Manufacturing Technologies

4.1 Improvement for Milling and Turning

The manufacturing process is selected automatically to keep the user interface concise and, in the future, to allow customers to upload multiple parts or entire assemblies at once without manually selecting the manufacturing technology for each component. During KPI determination tests, it was observed that clearly recognisable turned parts were sometimes identified as milled parts and vice versa. The algorithm analyses distances between features to identify a primary axis of the component, concluding it is a turning part. After the supplier updated the TICC software according to related recommendations, the 30 milling and turning reference parts of different complexity levels were correctly classified.

4.2 Additive Manufacturing

As for all selected manufacturing technologies, the same key performance indicator (KPI) has been defined to quantify the deviation between cost (c) estimation (index e) and the actual (index a) costs. The KPI (formula 1) is the standard deviation for samples based on the normalised deviation from its actual costs for each part. The KPI value decreases over time by improved cost calculation to reduce the safety margin, enabling a more competitive price without risking losses.

$$KPI_{Dev.} = \sqrt{\frac{\sum_{i=1}^{n}\left(\frac{c_{e,i}-c_{a,i}}{c_{a,i}}\right)^2}{n-1}} \tag{1}$$

A key characteristic of additive manufacturing (AM), especially for metals, is that such parts require a final machining step. Therefore, the Formal Quality Level (FQL) concept has been introduced, enabling an adjustment of the safety margin according to the availability raw and final part model [1], see **Fig. 3**. It is of significant benefit if the cost calculating tool receives both of the mentioned models instead of only the final part model (described in [4]). For this reason, the related design process [5] has been described in analogy to casting.

The related cost estimation tool is capable of handling raw and final part. The raw part is calculated in the AM module while the final machining takes place e.g. in the milling module. The latter is based on the volume difference between raw and final part model by taking the raw part as “raw material” in the calculation.

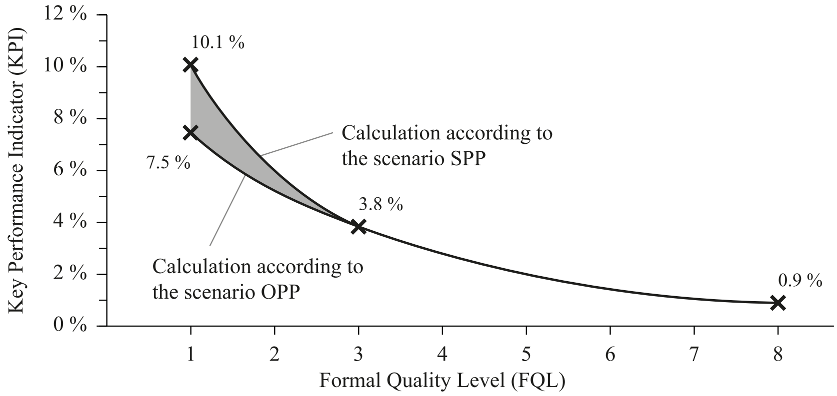

Fig. 3. KPI based on the FQL; Standard/Optimal Printing Parameters (SPP/OPP) [4]

4.3 Sheet Metal Cutting and Bending

The sheet metal processing module had to be developed almost from scratch. The calculation of cutting times were derived from recommended machine parameters of laser systems, such as those provided by Trumpf. These parameters consider material groups, different inert gases, cutting speeds (vary non-linearly with material thickness), cut quality requirements, and geometric precision. Additionally, the piercing time and the number of piercings is taken into account as the most time-intensive phase because the laser must penetrate a solid surface without an existing gap to evacuate molten material.

The bending module applies the concept for automatic bend recognition out of the bent model and not the flat pattern. This process is faster and less error-prone. For time estimation only, an exact flat pattern is not required, but for calculating the exact cutting geometry (correction factors for flap lengths) and for the bending process planning. Essential is the detection of the number of bends, their orientations, and the part size. Depending on the case, the time factor must be adapted, e.g. because two instead of one operator is required for large parts.

Another important factor is the number of tools required. Depending on bend length, tools of different lengths may be needed, especially when adjacent sides must be bent beforehand. Bend radii and accessibility also influence tool selection. Accurately determining this would require a full simulation of the bending process and strategy, as performed by specialised tools.

To enable automated cost calculation on a pragmatic basis, heuristic rules were defined. These consider that adjacent flanges often require additional tool setups, whereas similar bends can be executed with a longer tool set. For top-side accessibility, manufacturers typically use the longest gooseneck punches, so no differentiation is required.

This approach works reliably in most cases, although occasional improvisation by the manufacturer is still necessary. The resulting manufacturing time estimation is fast and sufficiently accurate. However, it does not detect non-manufacturable parts (e.g. intersecting flanges or impossible flat patterns). It was also observed that cost calculation philosophies vary significantly between manufacturers: some invest more time in setup and programming, while others emphasise actual bending time (**Fig. 4**)

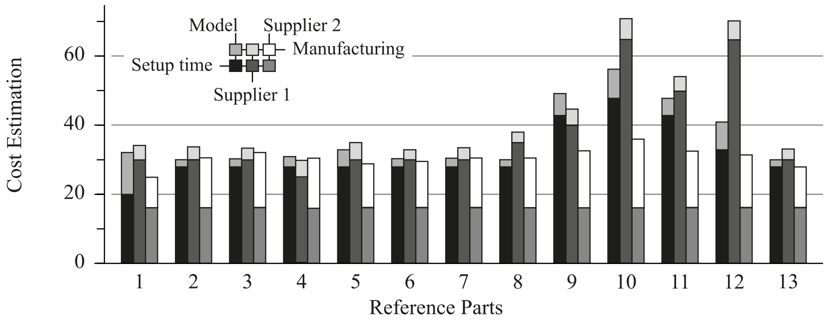

Fig. 4. Setup time and manufacturing costs for 13 reference parts with quantity 1 piece

The Key Performance Indicator (**Fig. 5**) shows a good performance of the model for supplier 1, whose cycle times closely match the predictions. Supplier 2, however, reports consistently low setup times but significantly higher per-piece cycle times, often 3 to 6 times above the model's estimates. This gap accumulates with every additional unit, leading to substantial deviations at higher lot sizes.

This highlights a broader challenge: true manufacturing costs depend on factors that suppliers themselves often cannot fully quantify. The actual cost of a part is influenced by whether similar orders can be batched together on the laser cutter, how efficiently remnant sheet material is reused across jobs, and whether the available press brakes are already equipped with the required punch and die sets, potentially reducing setup time to a fraction of the nominal value. Achieving better cost accuracy therefore requires not just refining the model but also gaining deeper insight into these shop-floor realities that are rarely reflected in standard quotations.

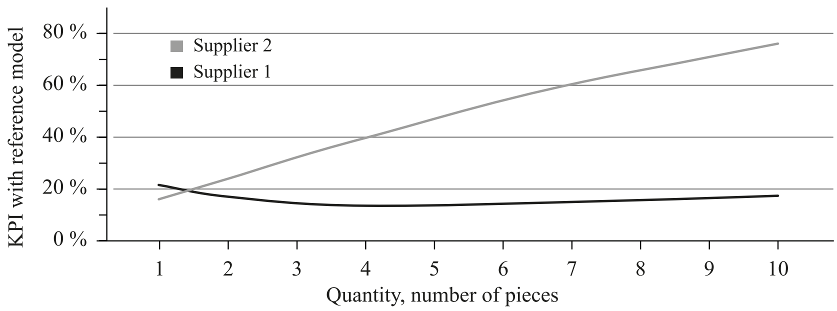

Fig. 5. KPI calculation referencing the model for supplier 1 and 2

5 Conclusions

5.1 Summary

A system was developed that enables automatic price calculation for parts manufactured using different production technologies. This establishes a platform capable of creating a marketplace that connects specialised suppliers according to their manufacturing expertise and available capacities. When analysing accuracy against manually calculated costs, especially in collaboration with sheet metal suppliers, it became evident that pricing philosophies differ significantly. In some cases, highly pragmatic values (e.g. for additive manufacturing) are used instead of mathematically derived figures. Overall, the automatically calculated costs for the reference parts fall within the range of manually quoted prices from specialists. A comparison with actual production costs was not possible within the project duration.

5.2 Outlook

While the platform achieved good stability and usability, the management of the industry partner unfortunately decided during this time to discontinue Real-Time Manufacturing and not to launch the expanded version, which included sheet metal processing and drawing interpretation, at all. In the future, the entire system is to be used internally at the ZHAW for the manufacturing laboratory. Since the ZHAW does not have to charge market prices but only internal costs, a precise cost analysis will be performed to allocate costs to the projects. This data will be used to further improve accuracy and therefore, to lower the KPI for all offered manufacturing technologies and related combinations as described in Chapter 4.2, page 7. Additionally, to achieve a higher Formal Quality Level (FQL) for AM improving the related cost calculation, establishing models for the raw and final machined part will be part of the education at the ZHAW.

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