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Automated Manufacturability Analysis for Conceptual Design in New Product Development

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Abstract

This paper presents ANA, a software package that provides automated manufacturability feedback to product designers, enabling first time quality of design and avoiding later stage change requests. Manufacturing knowledge is critical to the design process. Decisions made early in the conceptual design phase can significantly affect downstream production cost. Manufacturing engineers may have a limited role in the design process which can lead to designs that are difficult to manufacture. ANA is the implementation of numerous feature-free geometric algorithms that determine manufacturability metrics related to machining, casting, die-casting, and welding processes. These metrics are accompanied by colored 3D graphical models to provide rich feedback similar to finite element models, for example. The iterations of a design are tracked over time, allowing users to review how certain design decisions impact the expected manufacturability of the part. ANA is intended for use inside existing CAD systems, in the cloud, or as a standalone application. The feedback from ANA, combined with built-in learning modules, aids the user in making design improvements and assists in selecting an appropriate manufacturing process. This feedback can be shared across platforms via interactive 3D PDFs.

Keywords
Design for manufacturing, concurrent engineering, automation, engineering design, new product development

1. Introduction
Conceptual design is one of the first and most important phases in new product development (NPD), as all later activities are based on the initial design [1]. Decisions made early on NPD can lead to significant downstream costs in manufacturing, sourcing, or design rework. In an analysis of 2,000 parts designed by Rolls Royce, 80% of avoidable cost was attributed to design decisions, half of which was from design schemes as opposed to detailed drawings [2]. Designs that are difficult to manufacture can lead to not only increased manufacturing cost, but also costly engineering change requests. The practice of Design for Manufacturability (DfM) and Design for Assembly (DfA) were developed as methods to ensure product designs were able to be manufactured and assembled, reducing the product cost. In the early 1980's, Boothrooyd created one of the first systematic methods to evaluate and drive designs towards improved manufacture and assembly [3]. DfM and other Design for 'X' methods have led toward *concurrent engineering*, which seeks to consider multiple facets of a product's development throughout the design process. Effective use of DfM and concurrent engineering methods will improve manufacturability and reduce overall product cost [4].

Despite the benefits of DfM, product performance requirements often command the attention of the designer and management, leaving manufacturability as an afterthought. Many DfM tools currently on the market take a significant amount of time and data input to be used effectively. Materials, feature definitions, and GD&T are often required to provide a full DfM analysis. However, once these specific details have been determined, the general conceptual design of the part has already been decided during an earlier stage of the NPD process [1]. There is a need for DfM to be considered early on in the conceptual design stage before detailed drawings are finalized. DfM in this stage must rely on minimal user input, but provide feedback that can be used to improve the design of a part for specific manufacturing processes. The method presented in this paper, implemented as the ANA software platform, utilizes a fully automated process that provides process-specific feedback on arbitrary geometric models.

Rather than seeking to provide specific cost estimates, ANA is meant to be an early intervention tool that can catch manufacturing issues before detailed design has begun. The ANA software allows for customized manufacturing modules than can be added at any time to extend the manufacturing library of the software. Interactive graphical and numeric results are presented to the user, and progress of a design is tracked across iterations. The goal is for ANA to be used concurrently with CAD software as conceptual designs are being developed, providing automated analysis when desired by the user. The only input required by ANA is a geometric model of the part, in the form of an STL model. Automation reduces the burden on the design engineer, allowing them to focus on evaluation of the DfM results and on making improvements for the next iteration.

The rise of computing has allowed for the development of similar software-focused DfM methods. Two main strategies for analysis have been identified; *rule-based* and *plan-based* analysis [4]. Plan-based DfM seeks to analyze the design through inspection of a generated process plan. Rule-based approaches eliminate candidate processes based on certain manufacturing constraints. An example of rule-based analysis is the fast heuristics approach used by Kim and Simpson, which seeks to eliminate candidate processes based on information about the geometric model [6]. DfM systems that analyze the manufacturability of a model use geometric algorithms that are either *feature-based* or *feature-free*. Feature-based analyses seek to extract details about specific features of a model, such as an extrusion, hole, or plane. Information about the features is then used as an input to the analysis [7, 8]. Feature-based systems use methods to identify features from a model [9, 10], or rely on user input to specify information about the features [11]. In contrast to feature-based methods, feature-free geometric analysis works directly with a generic model of the design. Algorithms inspect the surface representation of the model to determine its manufacturability, and can handle any arbitrary geometry without requiring feature recognition. Most published work in feature-free DfM analysis focus on one specific manufacturing process, such as machining [12, 13, 14]. Many existing DfM systems are focused on analysis during the detailed design stage of NPD. As an example, ProMod provides a CAD based DfM environment for users to specify tolerances during detailed design [15]. Additionally, cost estimation has been attempted during new product development [16]. For example, Pro-DFM uses a variety of criteria to apply a penalty factor to a pre-determined baseline cost, and creates an estimate of the product cost based on procurement, fabrication/assembly, and inventory cost [17].

There is currently no feature-free DfM system that provides automated analysis for multiple processes during the conceptual design stage. ANA seeks to fill this gap by using a *characteristic-based* analysis that determines how able a part can be manufactured using a given process. ANA determines the "-ability" of a design to be made by a process, such as *machinability* or *castability*. As an example, *machinability* is defined as the relative ease at which the geometry can be produced using machining, and is correlated with the estimated cost. However, it is noted that not all cost can be determined during conceptual development, as detailed specifications like material and GD&T will significantly impact actual cost. The characteristics that define the manufacturability are determined from a combination of rule-based and plan-based aspects of the process. The algorithms are feature-free and work directly off the model provided, which enables early intervention feedback without requiring detailed user input. Normalized metrics provided by ANA can be used to help a designer select an appropriate manufacturing process, and the graphical feedback can help identify problem areas that would benefit from conceptual redesign before moving into detailed design. Lastly, ANA adds the capability to track the manufacturability of a design across iterations with an interactive dashboard.

2. Automated Manufacturability Analysis

The automated manufacturability analysis presented in this paper allows for forward-looking design decisions to be made during the conceptual design phase of new product development without requiring domain specific manufacturing knowledge. Rather than extract features from native CAD formats, ANA only requires a generic STL file as input, which is a facet-based representation of the design and the ad-hoc file standard in additive manufacturing. The STL standard is universal and can be converted directly from native CAD systems. Each manufacturing module within ANA performs DfM analysis on the STL file with respect to four characteristics that define the ability of a part to be produced by the given process. The DfM feedback is provided as a combination of colored graphical models, similar to those created by finite element analysis, and quantitative results. ANA works directly on a surface representation of the model so graphical results are colored on a per-facet basis. Each analysis also returns a normalized numeric score that measures the characteristic analyzed. These normalized scores are aggregated into a summative *manufacturability score* for the process. This normalized score can be used to compare the manufacturability of a design across iterations and across processes. Analysis for each manufacturing process is done by independent analysis modules. Any number of modules can be added to the ANA platform. The modules for casting, die-casting, and welding are currently under development. The machining module is nearing completion, and serves as an example of the type of feedback provided by ANA.

2.1 Machinability Analysis

Four characteristics that define the *machinability* of a part are determined as visibility, reachability, accessibility, and setup complexity. The machining module uses geometric algorithms to evaluate designs with respect to these four characteristics, which are meaningful indicators of the ease of machining a part. The following is a description of the four machining metrics.

Visibility: A part has a high *visibility* if the surface area of the entire model can be seen from the point of a view of a machine tool. Figure 1a shows a cross section of a model that is not completely visible, which ANA would detect as a problem area. ANA calculates a visibility level for each facet of the surface model and provides colored feedback to help the designer identify potential visibility issues. The visibility of a facet is defined on the range from 0-540 degrees, and is colored appropriately ranging from red to green. The value of 540 is based on a maximum of 180 degrees of visibility possible about the x, y or z axis of the part. As seen in Figure 1b, outer flat surfaces are completely visible from nearly any angle and are shaded green, while holes and inner features are shaded a darker red, indicating that the surfaces are only visible from a limited number of angles. Facets that are shaded grey are not visible from any angle, and represent features that may require redesign or another manufacturing process to create (for example, a cast-then-machine approach). The normalized score for visibility is the percent of the surface area of the model that is within the line of sight of a tool.

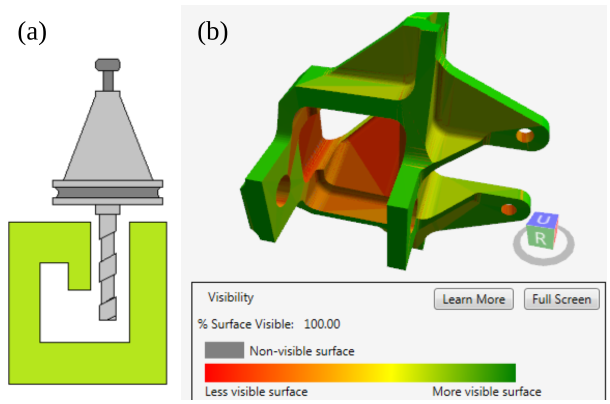

Figure 1: Visibility characteristic for machining. a) Example of problem geometry for tool line of sight. b) Colored visibility model feedback

Reachability: Reachability measures the length of tool that would be required to machine the surfaces of a model. Figure 2a provides an example of a surface with poor reachability, as a long tool is required to reach the bottom of the inner cavity. The reachability algorithm determines the shortest tool length that would be able to reach the surface, on a per facet basis. The colors are mapped to the model based on the depth, as shown in Figure 2b. Blue and green represents surfaces that can be reached with a short tool, while yellow and red indicates a longer tool is required. As an example, the yellow pocket in Figure 2b identifies an area requiring a tool length of over six inches. Surfaces that require a long tool during machining generally require slower feed rates and may cause dimensional non-conformance due to tool deflection. The required depth of each facet is aggregated into a normalized metric ranging from zero to one. The depth of each facet is weighted according to the surface area of the facet, and averaged across the entire model. A simple rectangular prism would have all of its surface area reachable with a short tool length, and would have a perfect reachability score of one. Parts with deep pockets would require longer tools and therefore have a lower score.

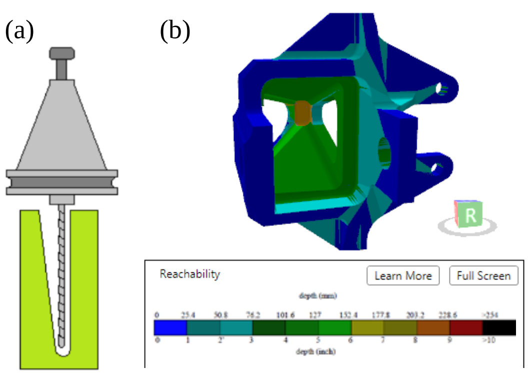

Figure 2: Reachability characteristic for machining; a) Part geometry with poor reachability, b) Color map of reachability depths

Accessibility: While reachability only accounts for tool length, accessibility measures the ability of a model to be machined without tool collisions. Figure 3a shows an example of geometry that may cause tool collisions when machined. Tool collisions are dependent on both the geometry of the surface and the tool diameter. ANA uses a slice based algorithm to determine which facets of a model might be inaccessible due to tool collisions. Facets of the model are colored red to indicate areas where a collision may occur. The red sharp corners on Figure 3b might indicate to a designer to consider adding a fillet, for example. The normalized metric for accessibility is similar to visibility, and is defined as the percent of the model's surface area that can be machined by a common commercially available tool (in this example a 1/4" end mill) without a collision. The algorithm is currently under improvement to provide a range of tool diameters, rather than just a binary result.

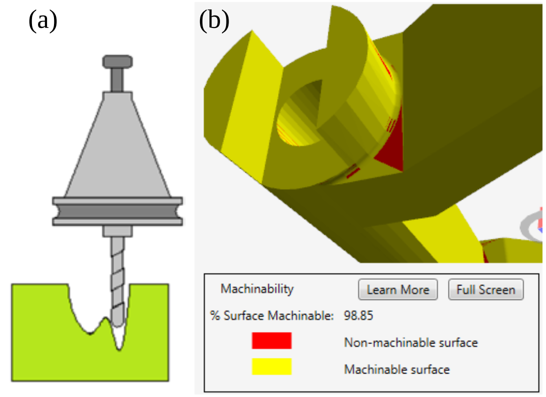

Figure 3: Accessibility characteristic for machining; a) Geometry with a tool accessibility issue, b) Color map of accessibility to facets

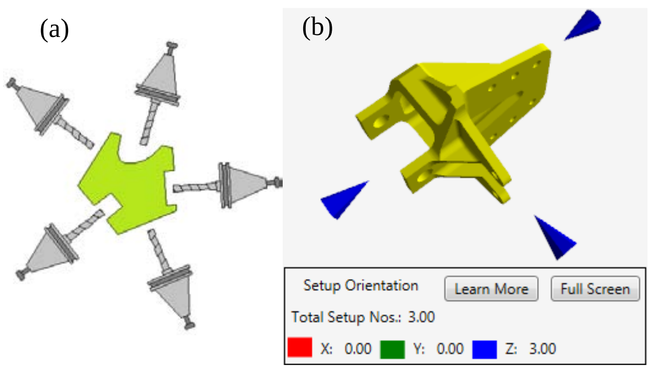

Figure 4: Setup complexity characteristic for machining; a) Geometry requiring multiple setup orientations, b) 3D representation of setup requirements

Setup Complexity: The number of setups required to machine a part can lead to increased cost. Complex models often require additional setups, as features must be rotated for a tool to gain access in a three-axis setup (Figure 4a). ANA uses heuristics to calculate a minimum feasible set of axes and rotations from which the model could be entirely machined. Figure 4b shows an example of a part's setup orientations analyzed by ANA, which can be machined using three discrete rotations along the Z axis. Parts requiring more axes and angles require either four or five axis mills, or additional human intervention in the form of manual re-fixturing and rotation operations for two or three-axis machines. The normalized score for setup orientations weighs axes and rotations separately, and is defined below in Equation (1).

$$Setup\ Complexity = W_A\left(\frac{A_{max} - A_{req}}{A_{max} - 1}\right) + W_R\left(\frac{R_{max} - R_{req}}{R_{max} - 2}\right) \quad (1)$$

Where W_A and W_R are the weights assigned to axes and rotations, respectively. The addition of W_A and W_R must sum to one to create a normalized metric. A_{max}, R_{max} and A_{req}, R_{req} represent the maximum possible and actual required number of discrete axes and rotations, respectively. The constants in the denominators represent the minimum possible number of axes and rotations. ANA assumes a discrete three axis setup (X, Y, Z), and eight possible rotations for each axis. This results in 18 total possible rotations for a given part (as six rotations are repeated). Equal weights are given to axes and rotations, and Equation (1) is resolved to Equation (2):

$$Setup\ Complexity = \frac{1}{2}\left(\frac{3 - A_{req}}{2}\right) + \frac{1}{2}\left(\frac{18 - R_{req}}{16}\right) \quad (2)$$

The four metrics; visibility, reachability, accessibility, and setup complexity, are aggregated into one composite *machinability* score ranging from zero to one, as shown in Equation (3).

$$Machinability = \sum_{i=1}^{4} W_i X_i \ni \sum_{i=1}^{4} W_i = 1 \quad (3)$$

Where X_i is the normalized score for metric *i* and W_i is the weight assigned to that metric. Current work involves determining weights for each metric that results in the best representation of machinability for the design, and investigating the impact of secondary effects that are amplified by combinations of certain metrics.

2.2 Tracking a Design across Iterations

Engineering design is an iterative process consisting of synthesis, analysis, and evaluation of subsequent designs (Figure 5). There is a benefit to understanding how design decisions at individual iterations impact the performance of the final design, and in the case of DfM, it is important for a designer to understand how decisions affect the manufacturability of the design. To facilitate this level of analysis, a dashboard has been developed to track manufacturability results across iterations of a design.

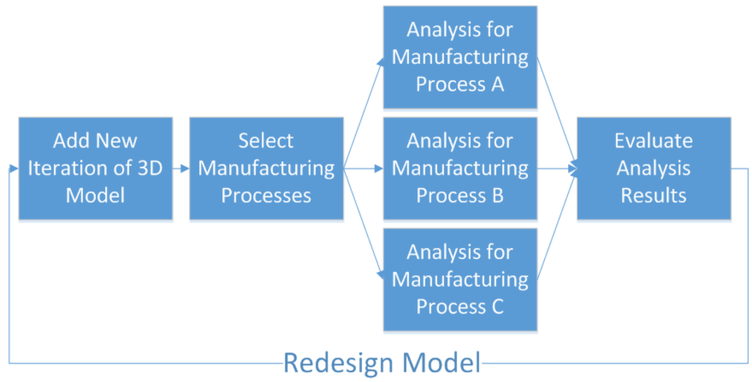

Figure 5: Information flow for automated manufacturability analysis

When the user has finished synthesizing a new iteration of a design, the 3D model (STL model) can be added to the dashboard as a new iteration. The user can select the desired manufacturing processes and run the analysis. Once the analysis is complete, the submitted 3D model is distributed to the selected modules. The modules run in parallel threads and return graphical and numeric results to the dashboard in a JavaScript object notation (JSON) format. After analysis is complete, the user can view the results for each process. This process of synthesis, analysis, and evaluation is repeated until the designer has converged on a final model. Throughout the process, the designer is able to look back and evaluate previous iterations of the design. The Dashboard allows users to view the designs of previous iterations, as well as a graph that tracks the change in the manufacturability scores for each process and for each characteristic within each process (Figure 6).

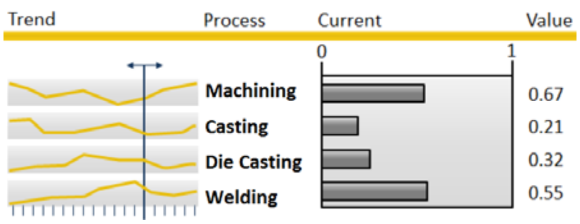

Figure 6: The ANA dashboard tracking manufacturability scores for each process and iteration

2.3 Communicating Manufacturability Results

While DfM feedback is useful to the product designers, the same feedback can be used to communicate with other stakeholders such as management, manufacturing, and sourcing. Consider the case of a foundry receiving an order from a customer. The part is not designed by the foundry, but the foundry is ultimately responsible for manufacturing the part. Graphical and numeric feedback regarding the *castability* of the part would be useful for explaining potential issues and negotiating prices. For example, if a part has many isolated heavy sections identified by the casting DfM module, it may show the customer that their design will require expensive risers. To facilitate this type of communication, DfM results can be exported to a portable 3D PDF file, shown in Figure 7. The PDF can be sent to all stakeholders, who can pan, rotate, and zoom to further inspect the manufacturability of the model.

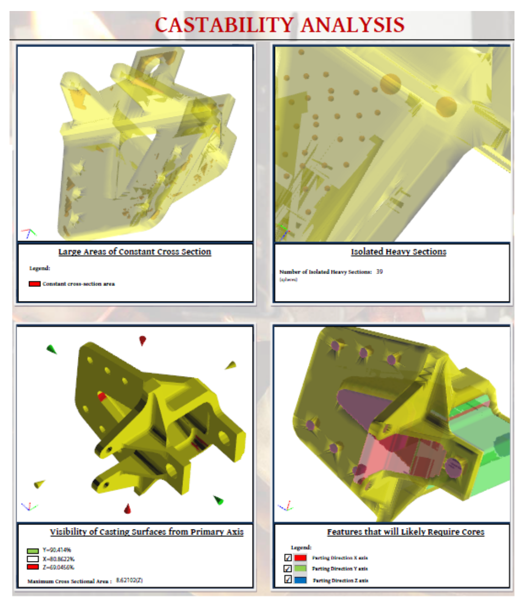

Figure 7: 3D PDF manufacturability results

3. Conclusions and Future Work

This paper presents a method for providing automated manufacturability analysis feedback during the conceptual design phase of new product development. Providing useful feedback at this stage not only improves the manufacturability of the end product but can reduce the number of engineering change requests that drive cost and risk into the new product development system. The ANA software platform provides visual and numeric feedback on any arbitrary geometry that can lead toward an improved design without requiring the user to have expert manufacturing knowledge. The dashboard calculates and tracks normalized scores that allow the user to compare the manufacturability of iterations and processes. ANA is the first software system that provides and tracks DfM feedback for multiple processes in the conceptual design stage and is expected to result in improved manufacturability of designs.

In its current state, ANA considers one process at a time, and does not analyze a design for hybrid manufacturing processes. Future work could include the creation of hybrid DfM modules that consider multiple processes in sequence, such as a casting followed by machining. Studies are underway to determine the optimal weighting for each manufacturability metric with regards to product cost. Future capabilities of the ANA system include integrating DfM feedback with existing enterprise data systems, such as those for supply chain management or environmental compliance. This may require input that goes beyond a sole STL file, such as material, expected production quantity, and desired lead time. While the current ANA system is intended as a DfM tool, it has the capability to serve as an extensible platform for multiple aspects of concurrent engineering, reducing the overall lifecycle cost of a product.

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References

1. Wang, L., Shen, W., Xie, H., Neelamkavil, J., and Pardasani, A., 2002, “Collaborative Conceptual Design–State of the Art and Future Trends,” Computer-Aided Design, 34(13), 981–996.
2. Corbett, J., and Crookall, P.R., 1986, “Design for Economic Manufacture,” CIRP Annals - Manufacturing Technology, 35(1), 93–97.
3. Boothroyd, G., 1994, “Product Design for Manufacture and Assembly,” Computer-Aided Design, 26(7), 505-520.
4. Doll, W.J., Hong, P., and Nahm, A., 2010, “Antecedents and Outcomes of Manufacturability in Integrated Product Development,” International Journal of Operations and Production Management, 30(8), 821–852.
5. Gupta, S.K., Regli, W.C., Das, D., and Nau, D.S., 1997, “Automated Manufacturability Analysis: A Survey,” Research in Engineering Design, 9, 168–190.
6. Kim, W., & Simpson, T.W., 2013, “Toward Automated Design for Manufacturing Feedback,” IFIP Advances in Information and Communication Technology, 414, 40–47.
7. Ramana, K.V., Singh, M., Gupta, A., Dey, R., Kapoor, A., and Rao, P.V.M., 2006, “A Manufacturability Advisor for Spun and Rollformed Sheet Metal Components,” International Journal of Advanced Manufacturing Technology, 28(3–4), 249–254.
8. Jacob, D.V., Ramana, K.V., and Rao, P.V.M., 2004, “Automated Manufacturability Assessment of Rotational Parts by Grinding,” International Journal of Production Research, 42(3), 505–519.
9. Jared, G.E.M., Limage, M.G., Sherrin, I.J., and Swift, K.G., 1994, “Geometric Reasoning and Design for Manufacture,” Computer-Aided Design, 26(7), 528–536.
10. Madan, J., Rao, P.V.M., and Kundra, T.K., 2007, “Die-Casting Feature Recognition for Automated Parting Direction and Parting Line Determination,” Journal of Computing and Information Science in Engineering, 7(3), 236.
11. Cutkosky, M., & Tenenbaum, J., 1992, “Toward a Framework for Concurrent Design,” International Journal of Systems Automation: Research and Applications, 239-261.
12. Lee, R.S., Lin, Y.H., Tseng, M.Y., and Wu, W.S., 2010, “Evaluation of Workpiece Orientation and Configuration of Multi-Axis Machine Tool Using Visibility Cone Analysis,” International Journal of Computer Integrated Manufacturing, 23(7), 630–639.
13. Samarghandy, H., and Li, Y., 2013, “Detecting Re-design Area for Increasing Manufacturability of Drilling and Three-Axis Pocketing Operations,” International Journal of Advanced Manufacturing Technology, 69(1-4), 337-349.
14. Barari, A., ElMaraghy, H., and ElMaraghy, W., 2009, “Design for Manufacturing of Sculptured Surfaces: A Computational Platform,” Journal of Computing and Information Science in Engineering, 9(June), 21006.
15. Nnaji, B., Liu, H., and Rembold, U., 1993, “A Product Modeller for Discrete Components,” International Journal of Production Research, 31(9), 2017-2044.
16. Geiger, T.S., and Dilts, D.M., 1996, “Automated Design-to-Cost: Integrating Costing into the Design Decision,” Computer-Aided Design, 28(6–7), 423–438.
17. Das, S., and Kanchanapiboon, A., 2011, “A Multi-Criteria Model for Evaluating Design for Manufacturability,” International Journal of Production Research 49(4), 1197–1217.