

1415 N CHERRY AVE
CHICAGO, IL 60642
(312) 281-6900
DMDII.ORG
DMDII@UILABS.ORG



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**DIGITIZING AMERICAN
MANUFACTURING**

DMDII FINAL PROJECT REPORT

DMDII 15-05-03:	
Lower Life-cycle Costs, Improve Design & Performance Robustness through the Digital Thread	
Principle Investigator / Email Address	Max Layman/Max.layman@rolls-royce.com
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I. EXECUTIVE SUMMARY

Current tools and methods used in the design of products and systems have **very limited capacity to support automated knowledge sharing** for decision making in life-cycle considerations. The deficiency is particularly acute at the **product subsystem/system level**. Therefore, there is **a need for solutions enabling digital integration of the wide array of stakeholders across the value chain**, including suppliers, and tracking the part/system variability impact on product life-cycle cost and performance. The data produced by existing information systems, such as computer aided design (CAD) and design for manufacturability (DFM) systems, are already in electronic format. But all the information required to make a decision may not be available, may lack consistency, and may not be expressed in a general format.

To address this deficiency, we have **developed and demonstrated an advanced pervasive systems architecture that would enable new technologies and models to be integrated within an original equipment manufacturer's (OEM's) product life-cycle feedback loop**. This would enable information and data integration across system and seamless feedback architecture through digital thread within an information technology (IT) structure accounting for proper intellectual property (IP) protection, export controls, and facilitation of optimization of lifing, performance, and cost. A high fidelity network system simulating the individual life-cycle stage (such as design, manufacturing, test, operations, etc) along with data and a knowledge converter module is wrapped into a "system framework" that has been exercised as required to enable optimization. The individual models incorporate process and data information relevant to the specific attribute/life-cycle stage. The data output from this simulation system is then converted into actionable knowledge to make decisions to improve design, manufacture, inspection, and assembly and to optimize the various interdependent "-ility" topics (e.g., system reliability, affordability) under consideration. Figure 1 shows the generic system framework.

The team consists of four levels of suppliers—Airframe OEM (The Boeing Company), Major Non-Aerospace Conglomerate (John Deere), Engine OEM (Rolls-Royce [program lead]), and Subject Matter Expert (SME) for Life Predictions of Gearbox Components (Sentient Science). The team also consists of Academia Members (Georgia Institute of Technology and The Pennsylvania State University). The proposed performance period was 18 months, with major milestones achieved in 12 months. The high level deliverables from this program are the following:

- **Generic Base Framework:** While a comprehensive digital network encompassing all aspects of the product life-cycle is a monumental task, the current program offers a generic, basic framework of a feedback network enabling information integration across the product life-cycle to enable the rapid use of actionable knowledge to improve and optimize design. The effort focused on gap analysis and the design of possible paths to bridge the gaps instead of addressing the procedural mechanics or the development of automated translators. The framework focused on translating compiled data from relevant sources into knowledge, which serves as a guideline for the engineering decision process.
- **Technical Demonstration:** A gear system demonstrator based on the generic framework to optimize reliability and sustainability was used.
- **Transition Plan:** A detailed plan to transition the generic framework into other systems used by the DMDII community is provided in this report. While the framework was demonstrated by using the gear system and designated software tools, the methodology was designed to be system agnostic that can be "retrofitted" into a wide variety of industry and part families.

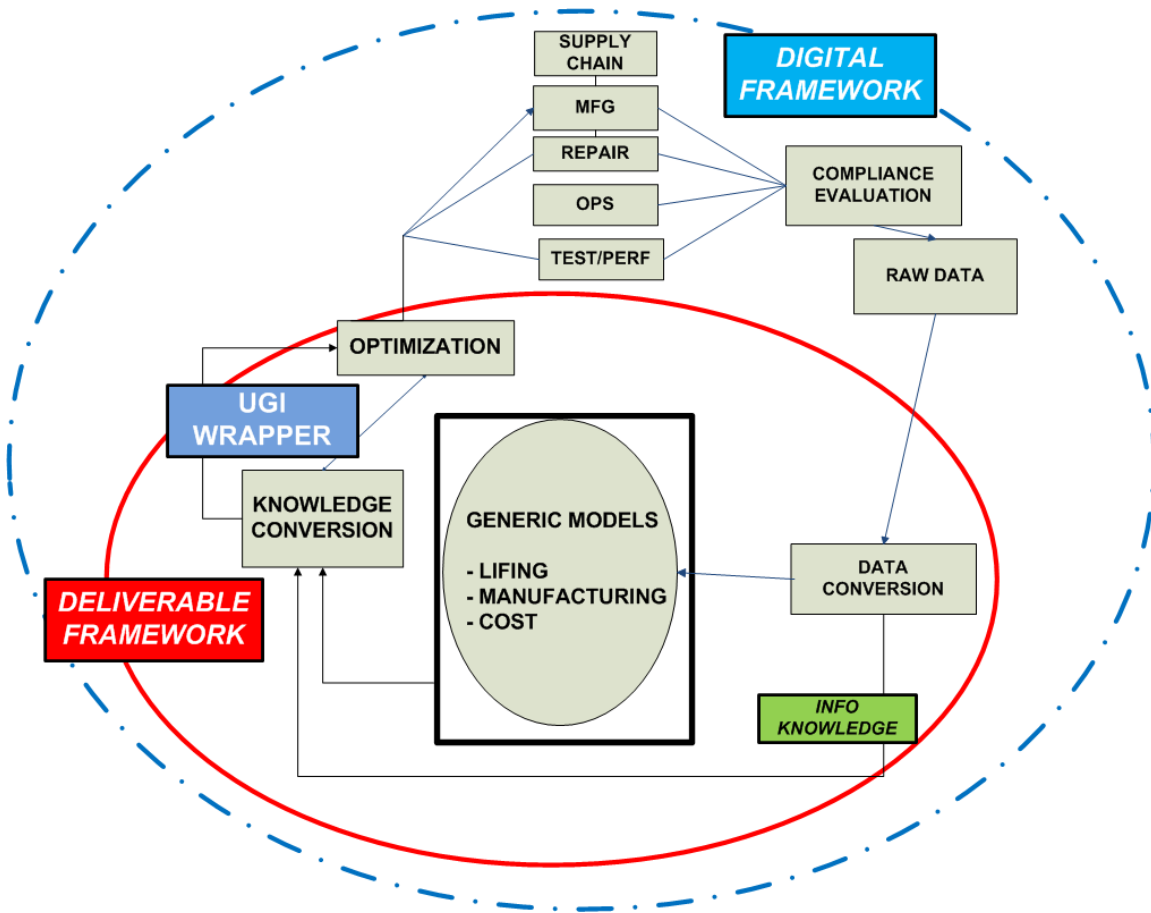


Figure 1. Generic system framework.

II. PROJECT REVIEW

2.1 Background and Challenges

Design requirements known as -ilities include producibility, serviceability, usability, sustainability, affordability, etc. Early considerations for -ilities in design would enable more producible, serviceable, usable, sustainable, safe, and affordable designs with shorter product development cycles and fewer design iterations. The common trend between the aerospace, industrial equipment, energy, and automotive industries is that operators are pushing their product capabilities as far as possible to increase performance. As power density and operating conditions increase, rotating systems and subcomponents like gears, shafts, and bearings and gearboxes themselves are increasingly the Achilles heel of these fleets. In addition, commercial operators are setting contracts where the penalty for failing to meet reliability and performance goals can result in serious financial costs for the OEM. There is a need for solutions enabling and integrating the wide array of stakeholders across the value chain, including suppliers, OEMs, and customers, and tracking part/system performance throughout the product life-cycle—as-designed, as-manufactured, as-shipped, as-installed, as-serviced, and as-disposed. There is a need for a digital framework linking information from manufacturing, inspection, supply chain, assembly, and subsystem/system operation relevant to design optimization trade studies in a seamless manner. The digital framework can then be exercised to efficiently evaluate the various -ilities during the system design phase itself.

Product design can influence a large portion of the product cost, so it is critical to obtain the cost estimates as early and quickly as possible during the design phase. Moreover, 80 to 90% of the time to market is used in the product planning and development phase due to the complexity of the product, and 40% of all the quality problems are caused by bad design. For example, a bad design can be the one that is not technically feasible. If a company wants to significantly shorten the time to market and enhance the quality of its product, one of many viable options is to try to enhance the efficiency and quality of the product design. Computer-based approaches are generally used to facilitate designers in reducing design time, decreasing product cost, and enhancing product quality. In the past 20 years, several computer-aided X (CAX) and design for X (DFX) tools have been developed for this purpose. All DFM systems share a common goal, which is to minimize the total product life-cycle costs through more systematic and efficient decision making when considering the design in light of manufacturing.

In product design, there are several technical and economic factors needing to be considered at the same time and these factors are related with each other. Facing the abundant data integrated from multiple data resources and the complex relations among them, designers also need support to make the decision in product design.

2.2 Current State

The current design and life-cycle management methodology is very linear and non-efficient. It involves many trial-and-error iterations, drives constant change, and tremendously increases the cost of sustainment because the current business units and business processes within large OEMs are siloed and do not communicate efficiently. Figure 2 shows the current state.

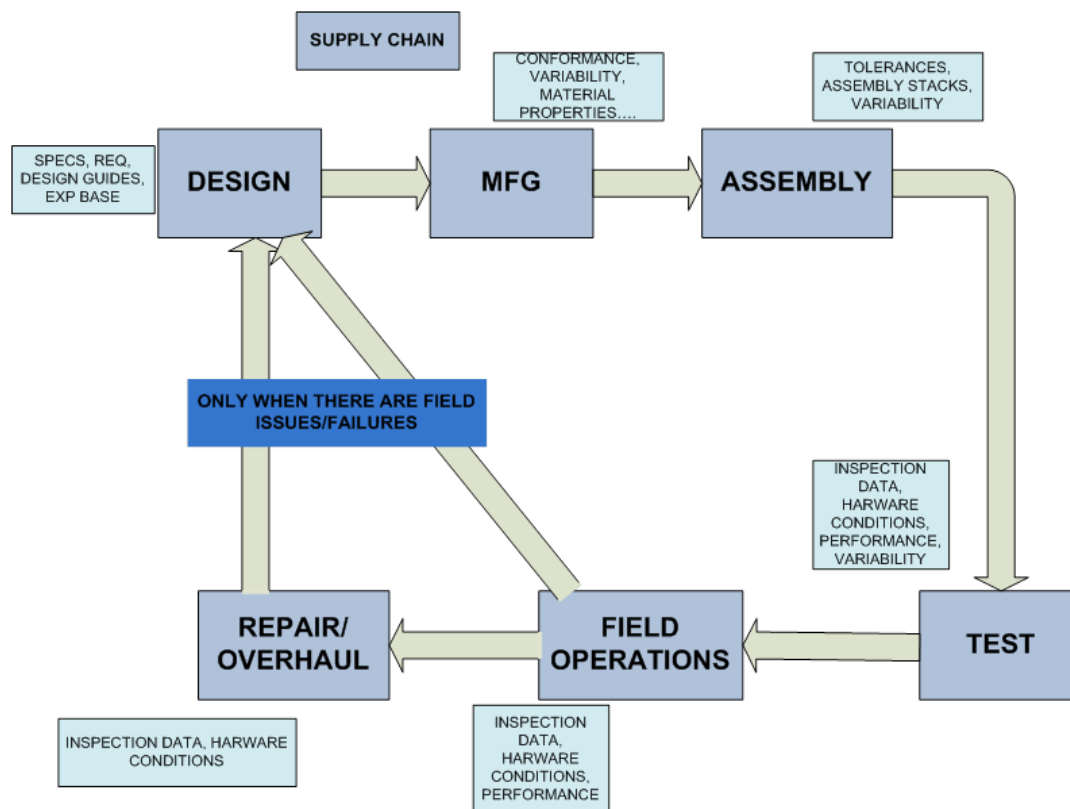


Figure 2. Current state of design and life-cycle management methodology.

At present, product designers are separated in different locations around the world and use multiple computer support tools to complete design tasks. The data created are saved in isolated and heterogeneous data resources, making it difficult to integrate information from data resources and obtain optimal designs. The purpose of this project was to explore the ontology-based method to enhance the consistency and availability of data, increase the efficiency of data utilization, and support the decision making of product design for product life-cycle. The field of DFM is used in the study, which includes the overall process of manufacturing and focuses on the technical and economic criteria in manufacturing. At the detailed design phase, OEMs are challenged to either increase production cost by overdesigning their systems or to increase the risk of future failures and future redesign, warranty, and operational and maintenance penalties throughout the product life-cycle by not overdesigning.

Today, approximately 70% of costs incurred over the life of a product are committed by decisions made during design. OEMs must make these decisions at the time of design because they cannot accurately predict the future life of their as-designed components, subsystems, and systems. Also, supply chain capabilities are not properly considered during the design phase. Current practice assumes that when each component conforms to the tolerance or assembly stack limits, there will be acceptable variability in the performance as designed. This is a lack of consideration from a system point of view. These tools also have very limited or no capacity to support real-time automated or semi-automated knowledge transfer from the other life-cycle stages for decision making based on life-cycle considerations. At the validation phase, OEMs use hardware testing to assess the life of each subcomponent based on a limited number of tests. There is no accounting for the variability in the as-made quality of the system because of the limited number of tests performed. At the manufacturing phase, OEMs start to see variability in the parts manufactured/procured due to the differences in tolerances of the various manufacturing processes. They primarily focus on inspecting each component as-made and pass/fail if they match with the as-designed specifications. Again, due to limitations in the inspection equipment and dimensionality, the system variability is not captured. But, during this late stage in designing a machine or system, there are still many choices for manufacturing processes based on their capabilities, including achievable dimensional tolerance, surface finish, production rates, and surface integrity (e.g., subsurface damage, residual stress), many of which can influence product performance and reliability.

When the components are assembled together into a system during the assembly phase, very limited high level inspections are conducted to ensure they meet the overall tolerance stack-up criteria. Greater variability is added in the process because it is not possible to understand how the realistic stacking of different subcomponents will interact and affect the performance and reliability of the full system. That is why from time to time a system built with good parts (conforming to the tolerance limits) could be under the performance requirement. The traditional design approach mainly focuses on the critical features and compliance of individual parts and often fails to account for the subsystem/system-level variability resulting from manufacturing, assembly, etc. This leads to additional failure risk being introduced into the product since the components cannot be matched and optimized based on their expected future life and tolerances. Then reactive correction actions will be needed to be carried out, which cost time/money and create dissatisfied customers. Many times these corrections are based on trial and error and tribal knowledge.

At the product launch phase, the compiled system is introduced to even more variability in the way that it will be used by the customer. Knowledge of customer use ranges from “high levels of knowledge” with regulated airline operations (for aircraft systems) to “relatively simple knowledge” with household/farm usage. As a result, designs are not optimized based on real-world feedback, which can result in increased warranty, sustainment costs, and reduced customer satisfaction and retention. Design for service is a

key element used to reduce warranty and sustainment costs, but very rarely is this conducted in conjunction with the other phases of the life-cycle.

In many cases, the relevant data and knowledge associated with the various stages of the design-production-service life-cycle are not readily available in standardized digital form to support -ility-based design trade studies. This is largely due to lack of a digital thread tying the various life-cycle stages to the design tool(s). In some cases, standardized digital representations/models that can serve as the basis for the creation of digital data repositories the design tool can access are not available. These deficiencies were addressed in the project.

2.3 Future State

To address the foregoing deficiencies, we have developed an advanced systems architecture that would enable new technologies and models to be integrated within an OEM's feedback loop (Figure 3). A systems engineering approach using the digital thread is a key element in the new architecture. This would enable information integration across the entire system and architecture for providing seamless digital feedback within an information technology (IT) structure accounting for proper intellectual property (IP), export control, and facilitation of life-cycle optimization. The first phase of the project was to formalize the final framework solution. There is an inherent recognition the system has "knowledge" of various forms – manufacturing, assembly, inspection, test, field operations, supply chain, and repair and overhaul.

A high fidelity network system simulating the individual life-cycle stage (such as design, manufacturing, test, operations, etc) along with data and knowledge converter models is wrapped into a "system framework", which has been exercised as required to enable optimization. The iterative process is contained within the virtual system. The individual models incorporate process and data information through the product life-cycle relevant to the specific attribute/life-cycle stage. The data output from this simulation model is then converted into actionable knowledge (not just a collection of data tables and/or curves) to make decisions to improve design, manufacture, inspection, and assembly and to optimize the various -ilities under consideration.

2.4 Gap Analysis

Comparing the current and future state maps, the existing main gaps can be classified into the three areas of Process, Technology, and Integration:

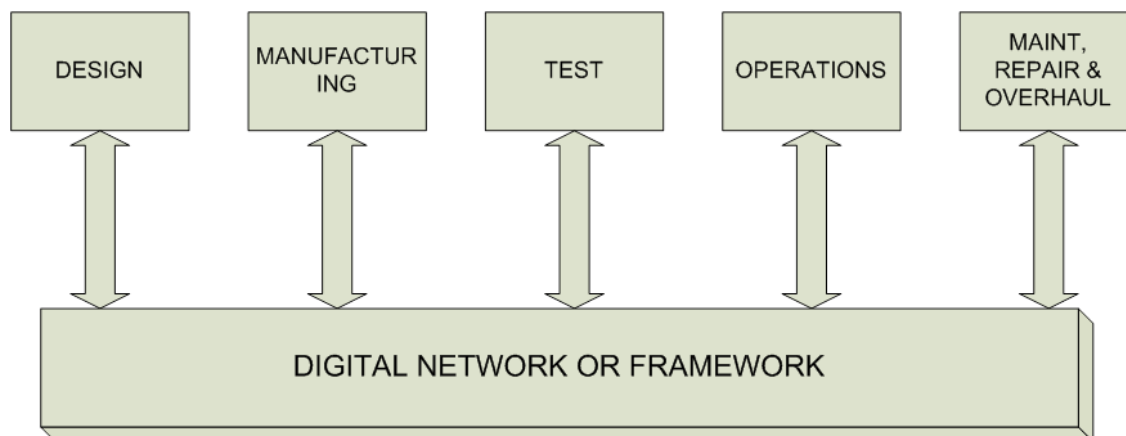


Figure 3. Future state integration.

- **Process:** Silo culture (internal and supply chain), design centric (lack of system-level thinking), lack of feedback from field to design, impact of part variations due to manufacturing and assembly on system performance and reliability
- **Technology:** Lack of system software, standardized representations/models for data/knowledge pertinent to manufacturing, subassembly inspection, data
- **Integration:** Lack of supply chain collaboration

2.5 Motivation and Benefits

Based on the gap analysis conducted, critical motivation factors and potential benefits of this project can be elaborated as the following:

- Right the first time
- Reduced development and sustainment costs
- Design optimized for reliability and sustainability
- An ontology that can help capture the domain knowledge in DFM and help designers make decisions based on technical and economic characteristics and relations
- Reduced life-cycle cost with improved performance
- Proactive versus reactive service support to customer
- Improved supply chain collaboration
- Increased product availability and agility in response to the customers
- Improved national competitiveness

III. KPI'S & METRICS

3.1 Project Deliverables

The project provides a digital framework for an advanced systems architecture enabling new technologies and models to be integrated within a OEM's feedback loop to enable optimization of various -ilities across a product's life-cycle (Table 1).

- The primary deliverable was generic framework architecture to enable this methodology to be applied to a wide variety of systems irrespective of the sector in which the products are used.
- A methodology for technology transfer to the DMDII community has been delivered. This is a combination of knowledge extraction technique, system level of variation management, product life-cycle feedback mechanism, and the associated training methods.
- For this project, we used a gear system subcomponent as a proof of concept of the architecture. The project deliverable was a gear demonstrator model that had been set up to optimize reliability and sustainability. A demonstration of the model was conducted at the DMDII Goose Island facility by the team in March 2018 during the technology showcase.
- As with any project, a set of monthly, quarterly, and annual reports were provided. At the end of the project, a final technical report (this report) was provided. Each report contained high level technical status, project risks and opportunities, schedule status and/or schedule modifications, project issues, budget expenditure, and cost share. Briefly these reports were:
 - Monthly technical reports
 - Quarterly technical and financial reports
 - Annual technical report
 - Final technical report

Table 1. KPI Metrics

Metric	Baseline	Goal	Results	Validation Method
Ability to take into account the performance, cost, and manufacturability for critical decisions	The current sequential consideration of KPI in a segmented approach	The ability to bring all relevant information on the dashboard interactively for effective decision making	The system wrapper took into account lifing, cost, and manufacturability to support decision making	The tableau based interactive GUI displayed interrelationship among the key variables
Applicability of the developed framework applicable for entire life-cycle	There is no existing framework in the open industry environment	The framework to be applicable for designing new product, enhancing existing design, and deciding on part repair/replacement	The system demonstrated three use cases: new design, design optimization, and repair/replacement support	The interactive GUI demonstrated with such capability
The framework is generic for a variety of part types/families	There is no existing framework in the open industry environment	The framework is pervasive, system agnostic, and part/process independent	The data and criteria can easily be replaced by other parts and/or processes.	The data and criteria can easily be replaced by other parts and/or processes
System optimization capability	Optimization in a manual and sequential fashion	The ability to optimize by considering performance, cost, and manufacturability simultaneously	The purpose of the program is not to automate but to facilitate; optimization is done by human	The system was validated by the team member companies
Effective user interface	Fragmented GUI (Graphical User Interface) for individual models	Visibility of all relevant KPIs in an interactive manner for what-if studies	Tableau was used as the interactive user interface with the relevant data and knowledge	Tableau is a proven tool in the industry

IV. TECHNOLOGY OUTCOMES

4.1 System Overview and Requirements

OEMs can reduce testing expenses and product launch time-to-customer by using computational performance testing to ensure the first design prototype meets its reliability (lifetime) requirements during the first hardware test and reduce the number of iterative loops within the design and at least the initial product launching phase. By using as-designed, as-made, as-assembled, and as-used data feedback and new physics-based models, engineers can perform effective trade-off studies via the digital thread. This enabling technology would be able to feed into cost and performance models and a data conversion process to provide knowledge as an output that can feed back to designers while they make decisions.

A set of generic gears, including their associated shaft, bearing, and housing, was chosen as the test vehicle because the gear system is very common throughout the industry. Traditionally, design incorporates the variability of the gears (tolerance) but the actual interaction between two engaging gears is a combination of the variability of gears, shafts, bearings, and the housing. This overall subsystem has direct impact on the part life, noise, vibration, and power transmission efficiency. The physics-based model (for prediction of gear system reliability in this project) becomes the standard for determining supplier qualification for a given application. With the system architecture shown in Figure 4, designers could have a decision support tool incorporating data from manufacturing, assembly, and operations and turning these data into knowledge that can be used in trade studies to measure the tradeoffs between affordability, performance, and reliability.

4.2 System Architecture

4.2.1 General Framework Overview

The Life-cycle and Cost Tradeoff Framework seeks to help solve one of the most prolific problems faced by designers: *How to design products that will last as long as possible, while reducing cost?* The framework presented in this section is generalized and could be applied in different areas (e.g., selecting manufacturing and usage requirements in early stage design and finding the desired manufacturing attributes for redesigns). The goal of the framework is to show to designers how changes in usage and manufacturing properties change impact life-cycle and cost. The designers will be able to use the framework to quickly predict how changes in these requirements will affect product quality and cost.

The Life-cycle and Cost Tradeoff Framework uses many individual models to predict key variables in determining the life-cycle and the total cost through the product's entire life-cycle. The smaller models are linked together to create a flow of information. This flow of information can be seen in Figure 4. Each rectangle represents a model, while the arrows represent the information going into or coming from the user or other models. The two green rectangles at the top are both cost models. The Manufacturing Cost Model estimates the per unit cost to manufacture the product. The Manufacturing and Repair Cost Model estimates not only the manufacturing cost but also the repair and replace costs for the product in the framework.

The Life-cycle Estimation Model estimates the life of the product or how long the product will continue to run until a failure. The model often can be used to predict a distribution rather than a single point,

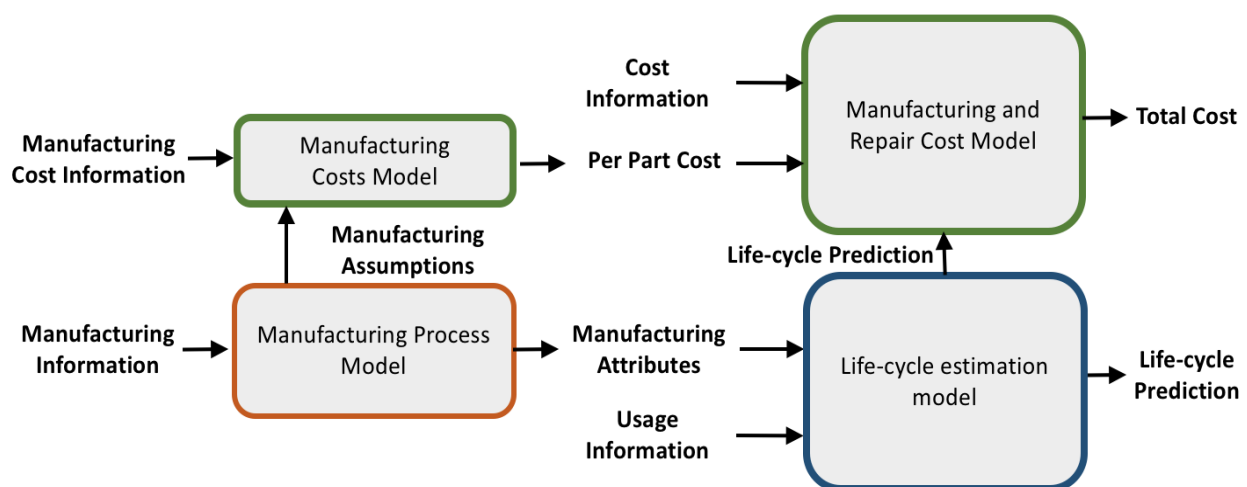


Figure 4. Life-cycle and cost tradeoff information flow.

such as an average. For instance, the model could predict a Weibull distribution and have strength and slope be the output variables.

The Manufacturing Process Model is a repository of manufacturing capability. This includes different sequences of manufacturing processes and the resulting manufacturing attributes. This will allow the user to select desired manufacturing attributes and tell the user if the process is feasible.

Since the framework is to be able to be generalized between industries, the models can be developed using a number of approaches. The first approach is a standard mathematical model. These are often industry defined standard equations and are well known. The second is a simulation model. These often take a Monte Carlo approach and use the inputs to sample many possible outcomes and return the results as distributions. The last model creation method is a data-driven or machine-learning based approach. These approaches can utilize simulated data or field data to develop complex models to try and approximate the relationships between inputs and outputs. These methods are often quicker at making predictions than simulations, but they are slower than standard mathematical models. However, many industries do not have standard mathematical models, so data-driven models are the best option.

To implement all of these models and store the information to support them, software-based architecture must be developed. Figure 5 shows one approach of implementing the models in the framework. The web-based user interface is on the left side in yellow, the server is in gray in the middle column, and the database is on the right column in light blue. The user specifies how the product will be used and the manufacturing requirements. The application then calls the server using the manufacturing model from the Application Programming Interface (API). The manufacturing model is able to check the manufacturing database to ensure there are manufacturing processes that can meet the desired requirements. The manufacturing attributes from the selected manufacturing process is returned and passed to the life-cycle model in the API. The life-cycle model calls the server, which returns the life span distribution given the manufacturing attributes and usage over the product's life. The unit cost from the

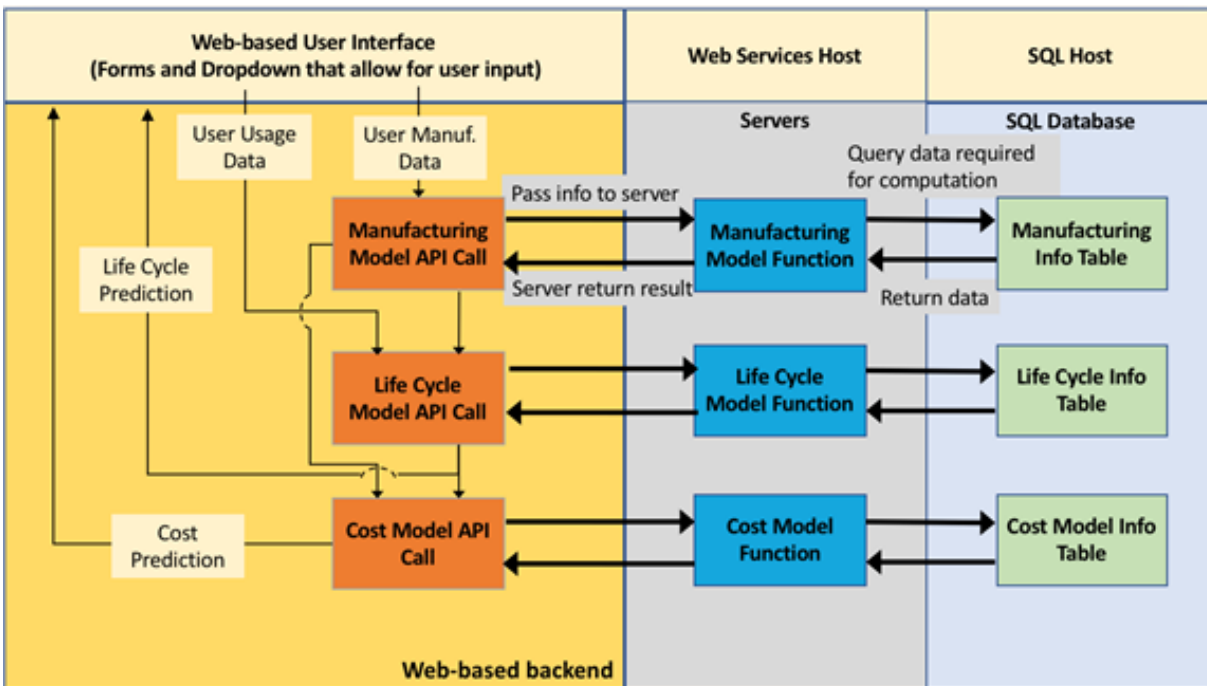


Figure 5. Life-cycle and cost tradeoff framework software implementation.

manufacturing function and the life prediction from the life-cycle function are then passed to the overall cost model. The cost model then returns the total cost of producing and maintaining the product over its life. Then the life-cycle prediction and cost value are returned to the user.

The Life-cycle and Cost Tradeoff Framework allows designers to conduct what-if analysis based on changes in usage, manufacturing attributes, and cost parameters. These what-if analyses will allow designers to get quicker feedback and therefore develop cheaper and longer lasting products.

For the demonstration phase of this project, we used a gear system subcomponent as a proof of concept of this architecture. We used these models to deliver what we call computational testing, that is, device testing done using computer simulations, to determine how the system would perform in actual operation. Gear system design, manufacturing, operational, and overhaul data were used as inputs into the system model, and simulations were conducted to optimize reliability and affordability. This demonstration focused on validating the functionality of the framework. It consisted of a subset of critical design and process parameters for the purpose of establishing a representative skeleton of the knowledge feedback methodology. Figure 6 provides an overview of the system model for the gear demonstrator. A full extent of data and knowledge related to the actual design of a specific gear subsystem is outside the scope of this project.

For this project, the models were created by the following entities:

- Manufacturing Process Model – Georgia Tech
- Life-cycle Estimation Model – Sentient Science
- Cost Model – Rolls-Royce
- Optimization – Penn State
- Wrapper – Boeing

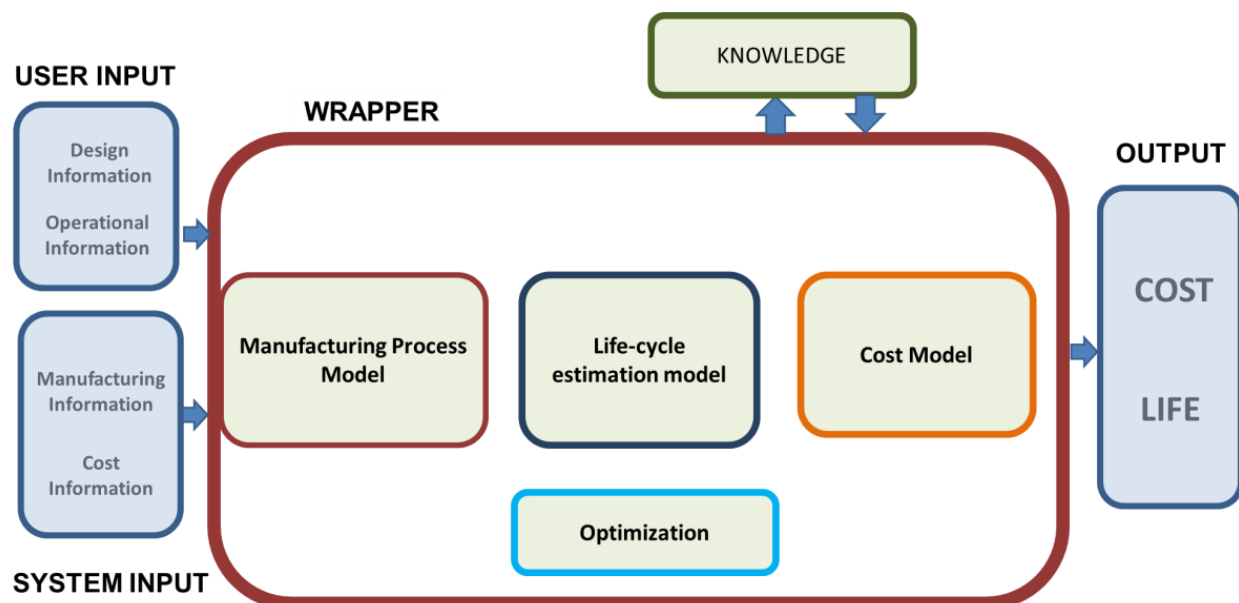


Figure 6. System architecture for gear demonstrator.

4.3 System Features and Attributes

4.3.1 Manufacturing Process Model

There are three components of the Manufacturing Model:

- Knowledge database
- HTML web interface through which users can interact directly with the knowledge database
- Web-based API enabling communication with other models and the wrapper developed by other project partners

Figure 7 shows a schematic to summarize the functionality of the three deliverables.

As shown in Figure 7, there are two primary means of interaction between the user and the Manufacturing Model:

- User can directly query the manufacturing knowledge database through the HTML web interface; the results from the database query are sent back to the user via the web interface
- User can query the manufacturing knowledge database via the wrapper, which communicates with the database through the web-based API

The following subsections provide an overview of the three components of the Manufacturing Model.

4.3.1.1 Features and Attributes of the Manufacturing Knowledge Database

In this project, gear and bearing ring manufacturing/repair processes were modeled to showcase the capability of the Manufacturing Model framework in the context of product life and cost trade studies. The core of the Manufacturing Model consists of the manufacturing knowledge database. The knowledge database contains a representation of the manufacturing knowledge relevant to the gear and bearing manufacturing use cases considered in the project. An ontological definition of each manufacturing process sequence is developed and stored in the Manufacturing Model, which serves as the core knowledge framework. Figure 8 shows an example of the gear manufacturing sequence ontology.

As shown in Figure 8, the ontology consists of the geometry, material, quality, production rate, and process cost attributes defining the capabilities of a gear manufacturing process sequence. The defined manufacturing process sequence ontology is represented in a SQL database, which ensures the Manufacturing Model can be easily instantiated, expanded, and accessed. In this project, the MySQL workbench was used to create the SQL database, and Figure 9 shows a screenshot of the workbench where the list of attributes represented in the manufacturing knowledge database can be seen.

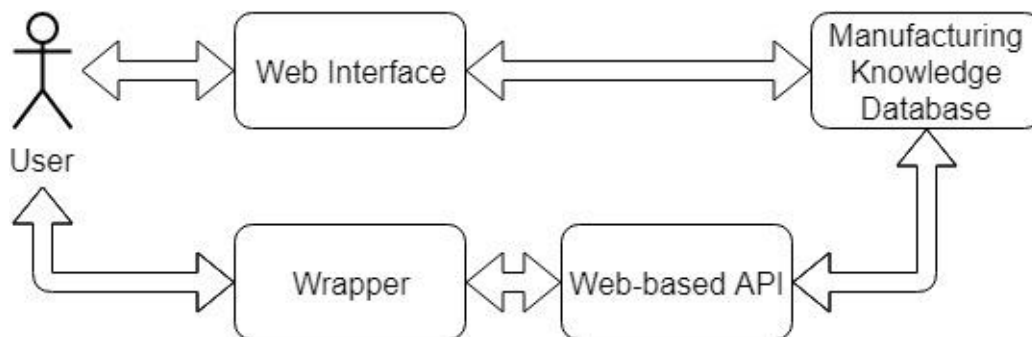


Figure 7. Modes of interaction with the manufacturing model.

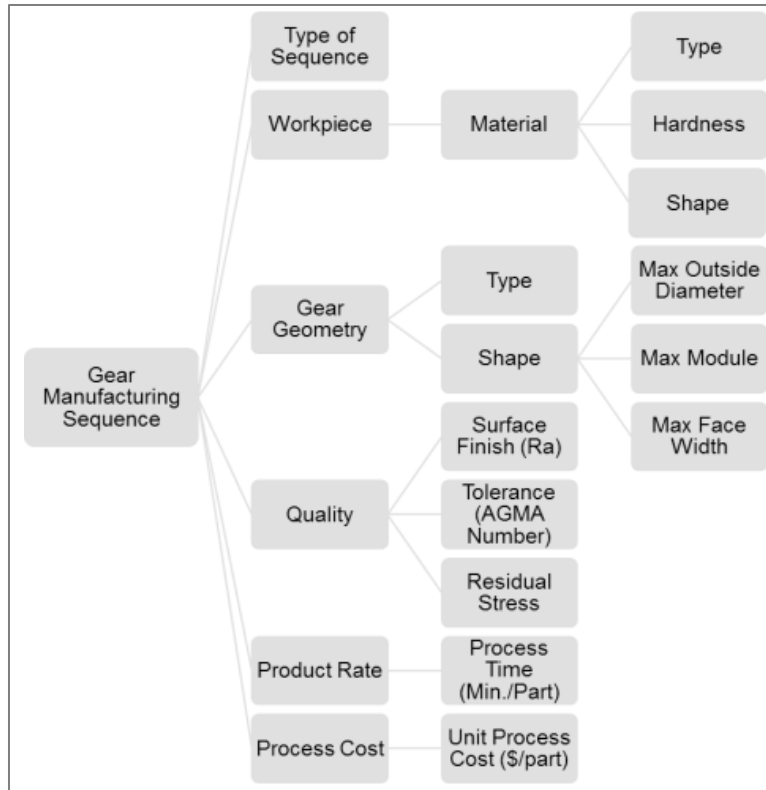


Figure 8. Ontology of a gear manufacturing sequence.

Column Name	Datatype	PK	NN	UQ	B	UN	ZF	AI	G	Default/Expression
id	INT(11)	☒	☒	☐	☐	☐	☐	☐	☐	
Pri	INT(11)	☐	☐	☐	☐	☐	☐	☐	☐	NULL
DisplaySequence	INT(11)	☐	☐	☐	☐	☐	☐	☐	☐	NULL
SequenceType	INT(60)	☐	☒	☐	☐	☐	☐	☐	☐	
SequenceName	VARCHAR(65)	☐	☒	☐	☐	☐	☐	☐	☐	
Note	VARCHAR(300)	☐	☐	☐	☐	☐	☐	☐	☐	NULL
Material	VARCHAR(70)	☐	☒	☐	☐	☐	☐	☐	☐	
MaterialTypeId	INT(60)	☐	☒	☐	☐	☐	☐	☐	☐	
Feed	VARCHAR(65)	☐	☒	☐	☐	☐	☐	☐	☐	
FinishingType	VARCHAR(70)	☐	☒	☐	☐	☐	☐	☐	☐	
MaxHardness	DECIMAL(65,0)	☐	☒	☐	☐	☐	☐	☐	☐	
OutsideDiameter	DECIMAL(65,0)	☐	☒	☐	☐	☐	☐	☐	☐	
MaxModule	DECIMAL(65,0)	☐	☒	☐	☐	☐	☐	☐	☐	
MaxFaceWidth	DECIMAL(65,0)	☐	☒	☐	☐	☐	☐	☐	☐	
Sa	DECIMAL(65,5)	☐	☒	☐	☐	☐	☐	☐	☐	
SaStd	DECIMAL(65,5)	☐	☐	☐	☐	☐	☐	☐	☐	NULL
ResidualStress	DECIMAL(65,2)	☐	☒	☐	☐	☐	☐	☐	☐	
ResidualStressStd	DECIMAL(65,5)	☐	☐	☐	☐	☐	☐	☐	☐	NULL
ResidualStressLocation	VARCHAR(100)	☐	☐	☐	☐	☐	☐	☐	☐	NULL
ResidualStressAccurate	VARCHAR(100)	☐	☐	☐	☐	☐	☐	☐	☐	NULL
ResidualStressAccurate1	DECIMAL(65,2)	☐	☐	☐	☐	☐	☐	☐	☐	NULL
ResidualStressAccurate2	DECIMAL(65,2)	☐	☐	☐	☐	☐	☐	☐	☐	NULL
ResidualStressAccurate3	DECIMAL(65,2)	☐	☐	☐	☐	☐	☐	☐	☐	NULL
ResidualStressAccurate4	DECIMAL(65,2)	☐	☐	☐	☐	☐	☐	☐	☐	NULL
ResidualStressAccurate5	DECIMAL(65,2)	☐	☐	☐	☐	☐	☐	☐	☐	NULL
ResidualStressAccurate6	DECIMAL(65,2)	☐	☐	☐	☐	☐	☐	☐	☐	NULL
ResidualStressAccurate7	DECIMAL(65,2)	☐	☐	☐	☐	☐	☐	☐	☐	NULL
Tolerance	DECIMAL(65,0)	☐	☒	☐	☐	☐	☐	☐	☐	NULL
ProductRate	DECIMAL(65,2)	☐	☒	☐	☐	☐	☐	☐	☐	
ProcessCost	DECIMAL(65,0)	☐	☒	☐	☐	☐	☐	☐	☐	
NumberOfSample	INT(11)	☐	☒	☐	☐	☐	☐	☐	☐	
MicroPittingMaxDepth	DECIMAL(65,2)	☐	☐	☐	☐	☐	☐	☐	☐	NULL
MCostEquation	VARCHAR(100)	☐	☐	☐	☐	☐	☐	☐	☐	NULL
SrMin	DECIMAL(65,5)	☐	☐	☐	☐	☐	☐	☐	☐	NULL
SrMax	DECIMAL(65,5)	☐	☐	☐	☐	☐	☐	☐	☐	NULL
CBase	DECIMAL(65,5)	☐	☐	☐	☐	☐	☐	☐	☐	NULL
Alpha	DECIMAL(65,5)	☐	☐	☐	☐	☐	☐	☐	☐	NULL

Figure 9. List of gear manufacturing process attributes represented in the manufacturing knowledge database.

As shown in Figure 9, specific instances of each manufacturing process sequence and the corresponding attribute values are stored in the knowledge database. Sequences of high level gear manufacturing process steps are represented in the knowledge database. Detailed definitions of the attributes can be found in Section XI of this document. Specifically, seven gear manufacturing process sequences, one bearing ring manufacturing process sequence, and four gear repair process sequences are stored in the knowledge database for the purposes of demonstration. Additional process sequences can be easily added to the database as new instances of process knowledge become available. For the purposes of the project, the specific values of the attributes of each gear process sequence stored in the database were obtained from literature or from data provided by project team partners. Representative values of the attributes for the bearing and gear repair sequences were derived from literature. Note the end user may easily replace these values with actual proprietary data from production.

4.3.1.2 Accessing the Manufacturing Knowledge Database via the HTML Web Interface

A web interface was created by Georgia Tech to enable direct user interactions with the Manufacturing Model. The web interface was coded using the PHP programming language. The web interface and the Manufacturing Model were implemented on Georgia Tech's public server and can be accessed through the following URL:

http://s10.fis.gatech.edu/DMII_GeorgiaTech_Demo_Homepage_VF.php#

Figure 10 shows a screenshot of the web interface. Using this interface, the user can perform the following manufacturing process sequence query:

Given the material type, outside diameter of the product, face width of the product, gear module, maximum allowable surface roughness of the product, maximum compressive residual stress, what are the available manufacturing sequences that can produce my design?

As shown in Figure 10, the user specifies the design inputs using drop-down menus and then clicks on the button "Click to see all applicable process" to find the candidate process sequences. The table in the middle of Figure 10 shows the available candidate sequences returned by the manufacturing knowledge database. The first column lists the IDs of each candidate process sequence, while the second column specifies the specific sequence options. To select a particular candidate sequence, the user inputs the corresponding ID into the textbox labeled "selected id" and clicks on the button "Click to see the final outputs" to obtain the corresponding capabilities of the selected gear manufacturing process sequence. Figure 11 shows a screenshot of the output page obtained for a selection of manufacturing sequence ID No. 3.

As shown in Figure 11, all the attribute values of the desired manufacturing sequence are output from the manufacturing knowledge database. The user can use these values to decide if he/she would like to proceed with the manufacturing sequence. Detailed definitions of the attributes can be found in Section XI of this document. The second functionality of the web interface is to update the existing data. At the bottom of the interface, there exists a hyperlink "Click Here to Add New Data to Update an Existing Manufacturing Sequence Data", shown in both Figure 10 and Figure 11. The user can click on the link to update the existing manufacturing sequence with new data. Figure 12 shows a screenshot of the updating function.

Figure 12 shows an example of the updating feature of the web interface. The user can insert the new attribute values to update existing data for a given gear manufacturing process sequence. The user then clicks the button at the bottom of the page to check if the updating data correlates well with the existing

s10.fis.gatech.edu/DMII x
s10.fis.gatech.edu/DMII_GeorgiaTech_Demo_Homepage_VF.php# ☆

Manufacturing Module Demo

Georgia Institute of Technology
Changxuan Zhao
Shreyes N. Melkote

Inputs:

Type of Manufacturing Sequence?

Material

Gear Outside Diameter (mm)

Gear Face Width (mm)

Gear Module

Maximum Allowable Surface Roughness, Sa (micron)

Minimum Allowable Residual Stress (Compressive), (MPa)

Note that all compressive residual stresses are negative values.

[Click to see all applicable process](#)

Select gear manufacturing/repair sequence Id from the following list

Id	Manufacturing Process Sequence	Description
3	Hobbing, Hardening, Grinding, Shot Peening	Baseline case
12	Hobbing, Hardening, Grinding, Shot Peening, Isotropic Finishing	Alternative case to study effect of surface roughness
13	Hobbing, Hardening, Grinding, Isotropic Finishing	Alternative case to study effect of residual stress
1	Hobbing, Shaving, Hardening, Shot Peening	
5	Hobbing, Hardening, Honing, Shot Peening	

Please enter the id number of the desired process which you would like to see the outputs

Selected id:

[Click to see the final outputs](#)

[Click Here to Insert A New Manufacturing Sequence Data.](#)
[Click Here to Add New Data To Update An Existing Manufacturing Sequence Data.](#)

Figure 10. Screenshot of the web interface for the manufacturing model.

s10.fis.gatech.edu/20180123_DMII_GeorgiaTech_Demo_Show_Result_P...

Manufacturing Module Demo

Georgia Institute of Technology
Changxuan Zhao
Shreyes N. Melkote

Outputs:

Selected Process Sequence:

Selected Feed for Hobbing Process:

Selected Finishing Process for Repair:

Process Cost (\$)

Production Rate (Part/Hour)

Surface Roughness Sa (micrometer) ±

Maximum Residual Stress (MPa) ±

Residual Stress Locations (micrometer from surface)

Corresponding Residual Stress At Measured Locations(MPa) , , , , , ,

Tolerance (AGMA Number)

Number of Samples Represented In this Data

[Click Here to Insert A New Manufacturing Sequence Data.](#)
[Click Here to Add New Data To Update An Existing Manufacturing Sequence Data.](#)

Figure 11. Sample screenshot of the output page when user selects the third manufacturing sequence.

Manufacturing Module Demo -- Updating Original Database

Georgia Institute of Technology
Changxuan Zhao
Shreyes N. Melkote

Sequence Id:

Max Hardness (HRC):

Outside Diameter (mm):

Max Module:

Max Face Width (mm):

Sa (micron): ± Standard Deviation of

Maximum Residual Stress (MPa): ± Standard Deviation of

Residual Stress Locations (micrometer from surface)

Corresponding Residual Stress At Measured Locations(MPa)

Tolerance (AGMA Number):

Product Rate (Parts/Hour):

Process Cost (\$/Part):

Number of Samples Represented In this Data:

Figure 12. Screenshot of the updating functionality of the web interface.

data in the database, i.e., if the deviation between the old and new attribute values fall within a predetermined acceptable range (20% in this case). The results of the check are shown in Figure 13. As shown in Figure 13, if the new data deviate more than 20% from the existing data, then user can either enter new data that are within the permissible tolerance or the user can ignore the warnings and proceed to update with the new data by clicking the button “Confirm and Update Manufacturing Database.” Note when new data updates the existing data, its impact depends on the number of data samples used to derive the existing and the new data. When a new data set associated with the manufacturing sequence is input to update the existing data, the following two equations are used to update the attribute values:

$$Attribute_{updated} = \frac{Attribute_{old} * N_{old} + Attribute_{new} * N_{new}}{N_{old} + N_{new}} \quad \text{Equation 1}$$

$$N_{updated} = N_{old} + N_{new} \quad \text{Equation 2}$$

where $Attribute_{old}$, $Attribute_{new}$, $Attribute_{updated}$ denote the attribute values of the existing data, that of the new data, and the updated attribute value. N_{old} , N_{new} , and $N_{updated}$ are the numbers of samples (or observations) used to determine the existing data, the new data, and the number of samples after the

Maximum Residual Stress (MPa): 1 ± Standard Deviation of 123

Residual Stress Locations (micrometer from surface) 0, 25, 76, 125, 256, 510, 1007

Corresponding Residual Stress At Measured Locations(MPa) 123 123 132 123 123 123

Tolerance (AGMA Number): 1

Product Rate (Parts/Hour): 1

Process Cost (\$/Part): 0.99186991869919

Number of Samples Represented In this Data: 1230

Check If New Data Disagree With Original Data

Maximum Hardness Does Not Agree With The Existing Data.

Outside Diameter Does Not Agree With The Existing Data.

Maximum Module Does Not Agree With The Existing Data.

Maximum Face Width Does Not Agree With The Existing Data.

Sa Does Not Agree With The Existing Data.

Maximum Residual Stress Does Not Agree With The Existing Data.

Tolerance Does Not Agree With The Existing Data.

Product Rate Does Not Agree With The Existing Data.

Process Cost Does Not Agree With The Existing Data.

Confirm and Update Manufacturing Database

Figure 13. Screenshot of the result of the checking function.

update. These two equations ensure the significance of the batch size of the data used to establish the attribute values. In practice, the batch size depends on the number of measurements (e.g., dimensions, surface finish, etc) made on the factory floor during inspection.

The third functionality of the web interface is to insert new manufacturing knowledge (or a new instance of a gear manufacturing process sequence available in the database). Figure 14 shows a screenshot of the web interface when performing the new knowledge insertion. As shown in Figure 14, the user can insert the new attribute values representing the new data into the knowledge database.

4.3.1.3 Accessing the Manufacturing Knowledge Database using the Web-based API

The third deliverable of the Manufacturing Model is a web-based API, which serves as an alternative method for the user to interact with the manufacturing knowledge database. The API was programmed

Manufacturing Module Demo -- Insert New Data

Georgia Institute of Technology
Changxuan Zhao
Shreyes N. Melkote

Sequence Type:

Sequence Option:

Material:

Material Type ID:
(Note: Insert 1 for "AISI 4320 Steel", 2 for "Other Material", 3 for "AISI 9310 Steel")

Feed for Hobbing Process(mm):
(Note: Insert "NA" for gear repairing process)

Finishing Method:
(Note: Insert "NA" for gear manufacturing process)

Max Hardness (HRC):

Outside Diameter (mm):

Max Module:

Max Face Width (mm):

Sa (micron): ± Standard Deviation of

Maximum Residual Stress (MPa): ± Standard Deviation of

Residual Stress Locations (micrometer from surface) 0, 25, 76, 125, 256, 510, 1007

Corresponding Residual Stress At Measured Locations(MPa)

Tolerance (AGMA Number):

Product Rate (Parts/Hour):

Process Cost (\$/Part):

Number of Samples Represented In this Data:

Figure 14. The inserting function of the web interface.

using PHP, and it automatically responds to the user's queries for information from the database or for editing the database. The API enables automatic flow of information between the different models developed by project team partners and thereby enables seamless model integration. The API utilizes the GET request feature of HTTP. Queries from the wrapper (or directly from other models) are routed to the API, which returns the responses in JSON format. The API is accessible via the following URL:

http://s10.fis.gatech.edu/20180208_API_Do_Whatever_You_Want/

The input query must be formatted as standard SQL statement, and the statement should be placed immediately after the URL to get correct responses from the API. Figure 15 shows an example query using the API. This example uses the RestEasy plug-in in Google Chrome. As shown in Figure 15, the

The screenshot shows a REST client interface. At the top, the URL is `http://s10.fis.gatech.edu/20180208_API_Do_Whatever_You_Want/SELECT SequenceName FROM geardemo WHERE id =3`. The method is set to `GET`. Below the URL bar are expandable sections for `Query Parameters`, `Headers`, and `Body`. At the bottom left is a `Clear` button, and at the bottom right is a `Send` button.

The response section is visible, showing a `Response Status: 200 (OK)` and a `Show Headers` button. The `Body` of the response is displayed in a text area:

```
[{"SequenceName": "Hobbing, Shaving, Hardening, Shot Peening", "0": "Hobbing, Shaving, Hardening, Shot Peening"}]
```

Figure 15. Example API query and response via RestEasy.

purpose of the query is to get the gear manufacturing sequence with ID No. 3. The corresponding attribute names in the manufacturing knowledge SQL database are `SequenceName` and `id`. Thus, the format of the query is as follows:

```
SELECT SequenceName FROM geardemo WHERE id =3
```

The corresponding URL containing the query to the API is:

```
http://s10.fis.gatech.edu/20180208_API_Do_Whatever_You_Want/SELECT SequenceName FROM geardemo WHERE id =3
```

The result sent back by the API is an array in JSON format as shown in the lower textbox of Figure 15. The array can be received and stored by the requester. This example validates the possibility of automatic information transmission between the Manufacturing Model, other models, and the wrapper.

4.3.2 Reliability/Life Model

4.3.2.1 Introduction to DigitalClone and Life Model

DigitalClone¹ is a physics and material science-based technology developed by Sentient Science that predicts the performance, quality, and reliability of rotating mechanical components such as bearings and gears. As shown in the following list, there are several advantages of using a physics and materials science-based computational testing approach as compared to conventional physical testing:

- Applicable to general problems and provides very precise descriptions of nature

¹ DigitalClone is a registered trademark of Sentient Science Corporation

- Does not rely on comparisons to experimental data or a table of interpolated values to produce results
- Produces better trends outside the database of available experimental results and reduces the error associated with extrapolation
- Can directly simulate the insertion of new technology and produce results for analysis
- Provides the capability for modeling a host of different conditions by rapidly changing the input or state parameters
- Generates detailed and comprehensive data, which can assist in explaining differences between expectations and results

Figure 16 outlines the framework used to combine physics with material science to predict component life. This framework has six steps. Step 1 is a macro analysis (global finite element analysis [FEA]) of the component under consideration subjected to various loading conditions. It is computationally intensive to perform fatigue damage analysis on global models, as a complete microstructure needs to be modeled. Hence, a representative volume element (RVE) is defined using Voronoi tessellation technique (the microstructure model: Step 2) to simulate fatigue damage. This submodel represents the high stress regions (critical sites for crack initiation) in the global FE model. In Step 3, surface traction profiles are generated by the mixed-Elastohydrodynamic lubrication (EHL) solver, if required in the application. In Step 4, these profiles are used to load the material model to perform microstress analysis at the grain level and update microstress fields as fatigue damage accumulates. This modeling approach is capable of estimating fatigue damage on a cycle-by-cycle basis to provide accurate life analysis. The number of cycles to crack initiation and propagation is calculated using stress field data at the nodal points of the mesh in the RVE microstructure model (Step 4). Iterative simulation in Step 4 is repeated until a final failure happens, resulting in the total fatigue life at the end of simulation, which is Step 5. Different RVEs are generated for each fatigue life simulation to capture the variability in material microstructure, properties, and surface finish using probabilistic methods. This will provide the fatigue life distribution (Step 6).

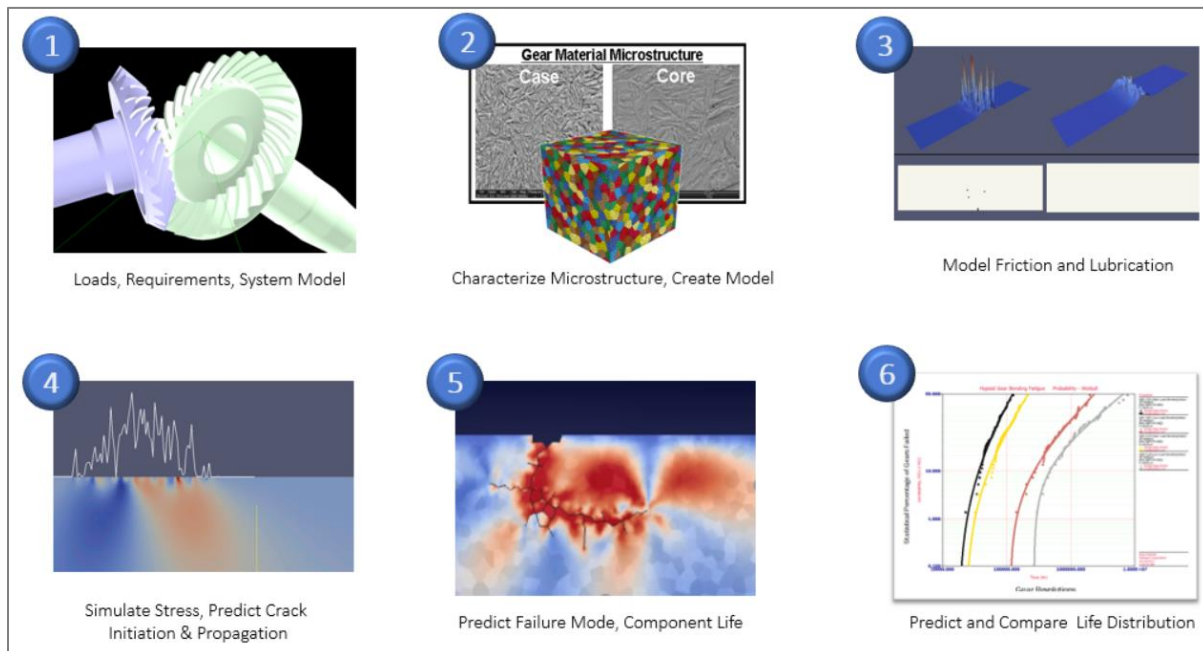


Figure 16. DigitalClone six-step process.

Within the project framework, DigitalClone technology is utilized to conduct lifing and sensitivity study on two gears supplied by John Deere. Simulations were conducted on the two gears to evaluate baseline conditions, and then sensitivity analysis was done on one gear by varying the following parameters:

- Manufacturing Process (changing surface roughness and/or residual stress)
- Load (applied torque)
- Misalignment (assembly misalignment)

4.3.2.2 Detailed Description of the DigitalClone Process

4.3.2.2.1 Gear Geometry and Operational Data

Detailed gear geometry was used in the analysis to obtain accurate contact conditions – contact pressure and sliding velocities. The list of the parameters used in DigitalClone component stress analysis is provided in Table 2. These data were provided by John Deere for both Gear 1 and Gear 2.

Figure 17 shows a result of the component stress analysis and a comparison of component stresses between Gear 1 and Gear 2. Contact stress distribution across the gear tooth is obtained for each gear.

Table 2. List of geometry and operation parameters provided by John Deere.

Number of Teeth	Tip Relief Roll Angle (deg)	Center Distance (mm)
Normal module (mm)	Tip Relief Magnitude (mm)	Gears Axial Offset (mm)
Normal Pressure Angle (deg.)	Root Relief Length (mm)	Misalignment (mrad)
Normal Helix Angle (deg.)	Root Relief Roll Angle (deg)	Speed (rpm)
Outside Diameter (mm)	Root Relief Magnitude (mm)	Torque (N.m)
Root Diameter (mm)	Flank End Relief Length (mm)	
Profile shift	Flank End Relief Magnitude (mm)	
Fillet Radius (mm)	Crowning Magnitude (mm)	
Face Width (mm)	Nominal Pitch TT (mm)	
Tip Relief Length (mm)	Normal Backlash (mm)	

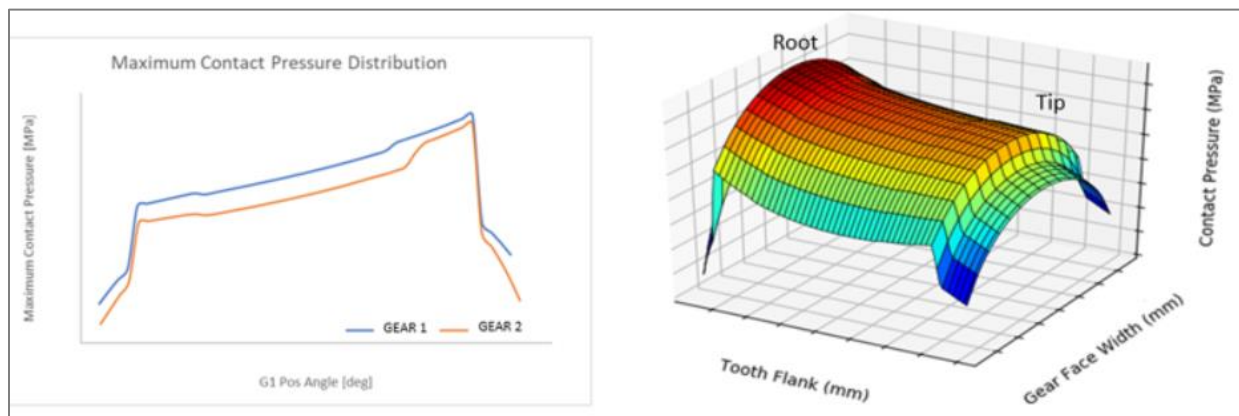


Figure 17. Comparison of maximum contact pressure with respect to the gear position angle (left) and an example of contact pressure distribution over the gear tooth(right)

It can be observed that the maximum contact pressure of Gear 1 is slightly higher as compared to Gear 2 as the gears mesh and share loads. This difference results from differences in geometrical parameters listed in Table 2.

In addition, the surface velocities are also obtained, and they are a function of the gear geometry and operating conditions as shown in Figure 18.

The contact pressure and surface velocities thus obtained across the gear tooth are inputs to the DigitalClone fatigue model.

4.3.2.2.2 Gear Material Characterization

To consider the effect of material microstructure and effect of variability in fatigue life due to the microstructure, a detailed material characterization is conducted. Typical observations made as a result of material characterization are the following:

- Hardness profile versus depth
- Residual stress profile versus depth
- Surface roughness distribution (RMS, Skewness, Kurtosis, and Autocorrelation parameters)
- Grain size distribution
- Microstructure type and composition and information on different phases
- Inclusion size and density
- Other microstructural defects such as retained austenite, grind burn, IGO, etc

Figure 19 shows comparison of hardness profiles between Gear 1 and Gear 2. From the microhardness measurements, Gear 2 exhibits higher hardness values and a higher case depth as compared to Gear 1.

Figure 20 shows the comparison of residual stress profiles between Gear 1 and Gear 2. From the measurements, it is observed both gears exhibit similar residual stress profiles but Gear 1 has higher compressive stresses and also maximum compressive stress as compared to Gear 2. Residual stress is a direct input to the DigitalClone model.

Surface roughness measurements are conducted using 3-D white-light interferometry. Multiple observations across the gear tooth are conducted to obtain surface roughness distribution parameters such as RMS roughness, skewness, kurtosis, and autocorrelation. An example surface roughness image

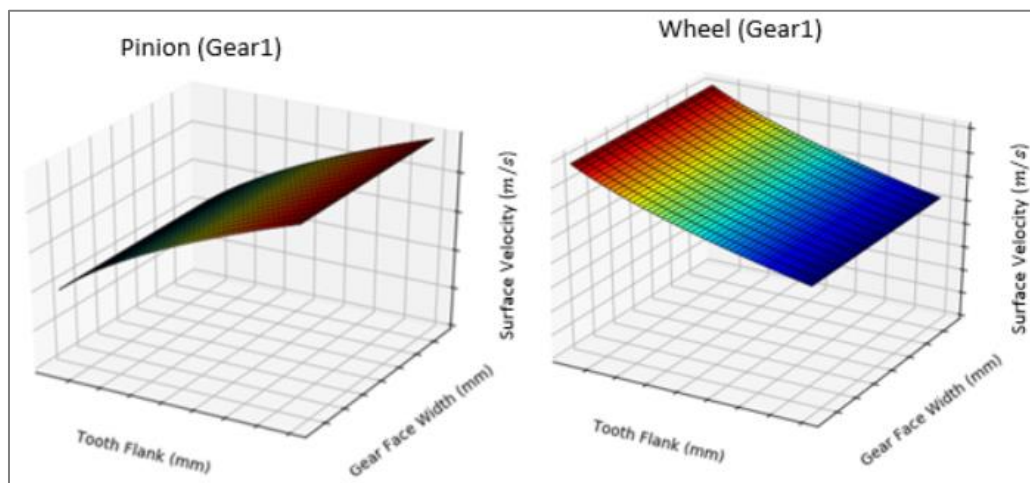


Figure 18. Surface velocities of the meshing gears.

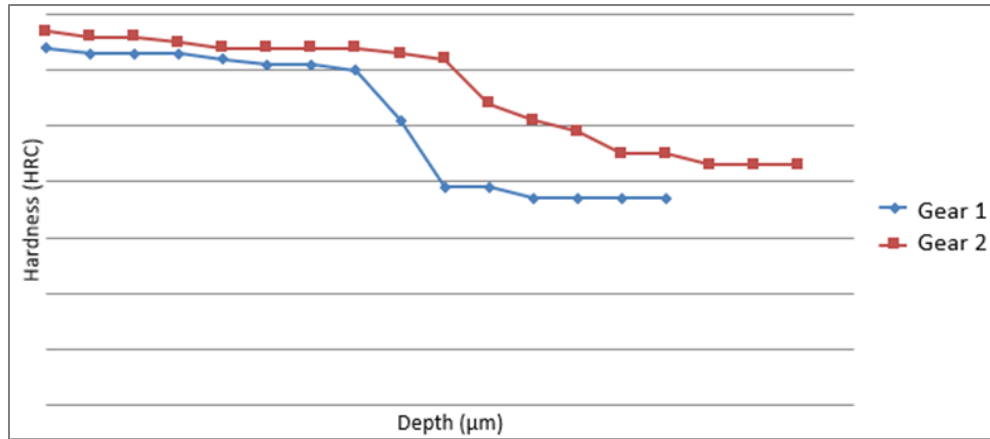


Figure 19. Microhardness profile versus depth.

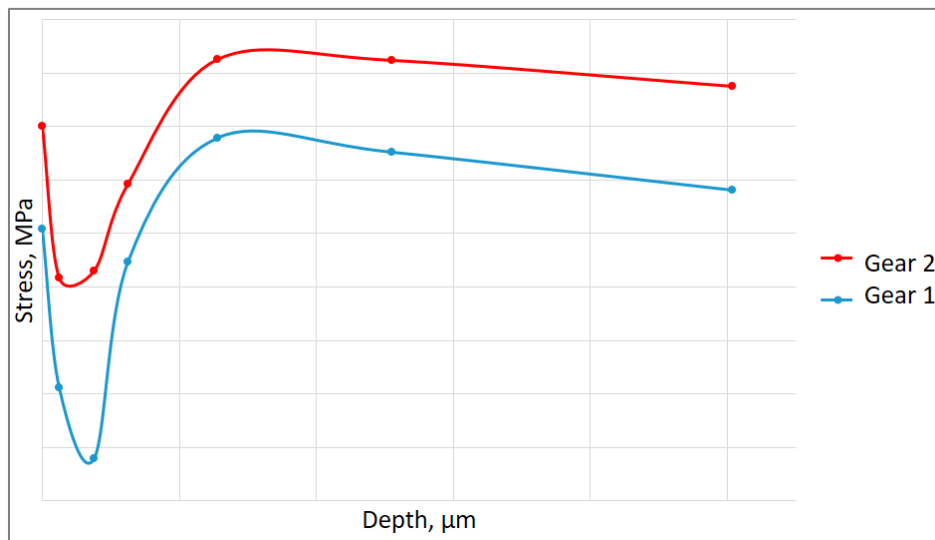


Figure 20. Residual stress profile versus depth. All values are compressive.

as obtained on gear 1 is shown in the Figure 21. From surface roughness measurements, RMS surface roughness of Gear 1 (0.8 - 1.0 μm) is higher than Gear 2 (0.5 - 0.7 μm).

Etched and unetched samples of the Gear 1 and Gear 2 materials are observed under optical microscope to obtain information related to grain size, defects, and inclusions in the material. Figure 22 depicts an example analysis and comparison of Gear 1 and Gear 2.

The hardness profile, residual stress profile, surface roughness distribution, and results of optical microscopy on etched and unetched samples are used to create a material model that is used in DigitalClone fatigue life simulations.

4.3.2.2.3 DigitalClone Fatigue Life Simulations – Lubrication Model

A mixed-EHL simulation is conducted to consider the effect of surface roughness and lubricant. The contact conditions obtained from component stress analysis are used as an input in this model. The surface roughness parameters measured during the material characterization step are also utilized here along with the lubricant properties (viscosity and pressure-viscosity coefficient), which were provided by John Deere.

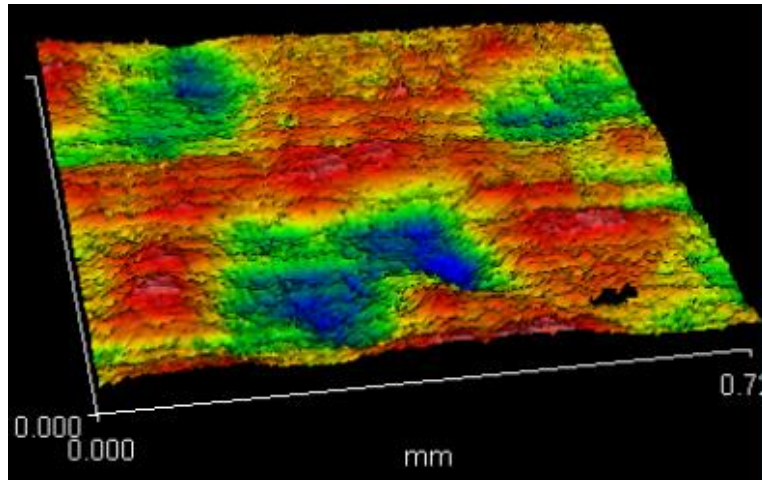


Figure 21. Image of surface topography obtained from an optical profilometer.

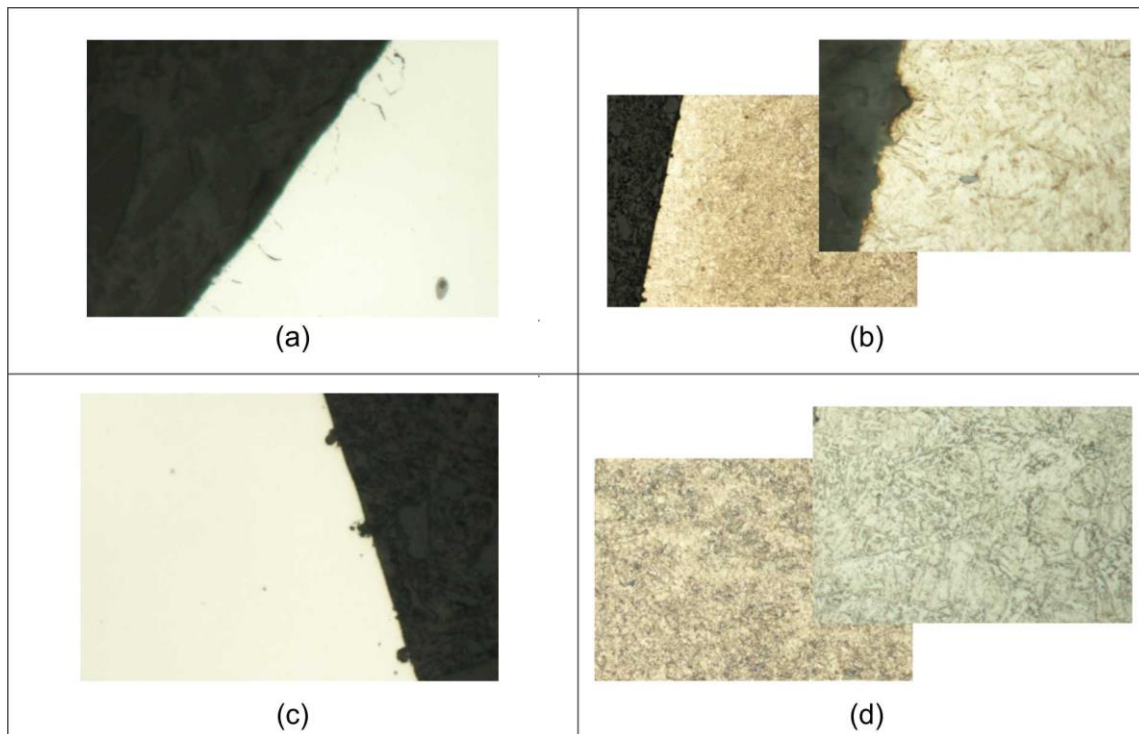


Figure 22. Optical microscopy of etched and unetched samples: (a) Gear 1 unetched, (b) Gear 1 etched, (c) Gear 2 unetched, and (d) Gear 2 etched.

The following observations are made from this analysis step and illustrated in Figure 23:

- Transient film thickness reveals film breakdown at the positions of asperity contact
- Two- to three-fold increase in contact pressure profiles during asperity interaction
- Asperity interactions are more severe in Gear 2 when compared to Gear 1

Figure 23 shows the film thickness profile resulting at the contact between two gears. The combined effect of surface roughness and lubricant properties are considered in this model. It can be observed there are severe asperity contacts in both the gears, however, the asperity contacts are more severe in Gear 1, which has higher roughness as compared to Gear 2. An average contact pressure profile in 2-D is

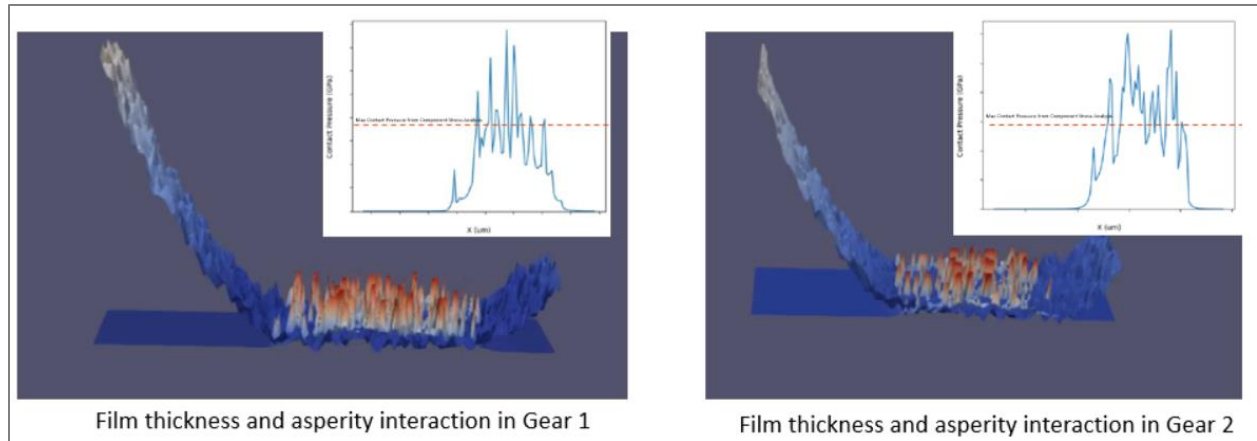


Figure 23. Comparison of film thickness profiles, asperity interaction (shown as peaks in red) and average contact pressure profile between Gear 1 (left) and Gear 2 (right)

extracted from the simulation to illustrate the observation of high contact pressures at points of asperity interactions, which are two to three times higher than the nominal contact pressure (shown by red dotted line) calculated during component stress analysis.

4.3.2.2.4 DigitalClone Fatigue Life Simulations – Material Damage Model

In the final step of the DigitalClone simulations, the results from material model created by material characterization are combined with the results from lubrication model to predict crack initiation and crack propagation in the material domains. Multiple simulations are conducted to account for the variability in material microstructure. Figure 24 shows a scenario when the crack originated on the surface resulting in a pit/spall depth of 71 μm , while Figure 25 shows a scenario when the crack originated in the subsurface resulting in a pit/spall depth of 276 μm . Based on the analysis of multiple such simulations, it is determined the critical failure mode in the gears are pitting/spalling.

Once multiple simulations per gear are conducted, the fatigue life distributions are fitted to a Weibull three-parameter distribution. Reliability estimates can be conducted using these data, and the same data are also used in cost models. In this project, L10 life (life that 90% of the gears in the sample population will reach or exceed) is derived out of the distributions and compared. The comparison of fatigue life distribution of Gear 1 and Gear 2 is shown in Figure 26. It was observed the L10 life of Gear 2 is 3.1 times higher than the L10 life of Gear 1.

Higher life of Gear 2 most likely resulted from:

- Higher case microhardness and deeper case depth
- Less oxidation near surface
- Better surface roughness
- Lower contact pressure

The surface roughness parameters and residual stress profiles for Gear 1 (GB1) and Gear 2 (GB2) baseline were obtained by Sentient Science by conducting detailed material characterization of the gears. The details are shown in Table 3.

Table 3. Results from material characterization of gears.

	Gear 2 Baseline	Gear 1 Baseline	Manufacturing Model
Depth	RS1 (MPa)	RS2 (MPa)	RS3 (MPa)
0	-180 to -220	-380 to -420	-670 to -680
25	-460 to -500	-670 to -710	-60 to -70
75	-450 to -490	-800 to -840	-20 to 0
125	-300 to -340	-440 to -480	30 to 60
250	-50 to -90	-200 to -240	30 to 60

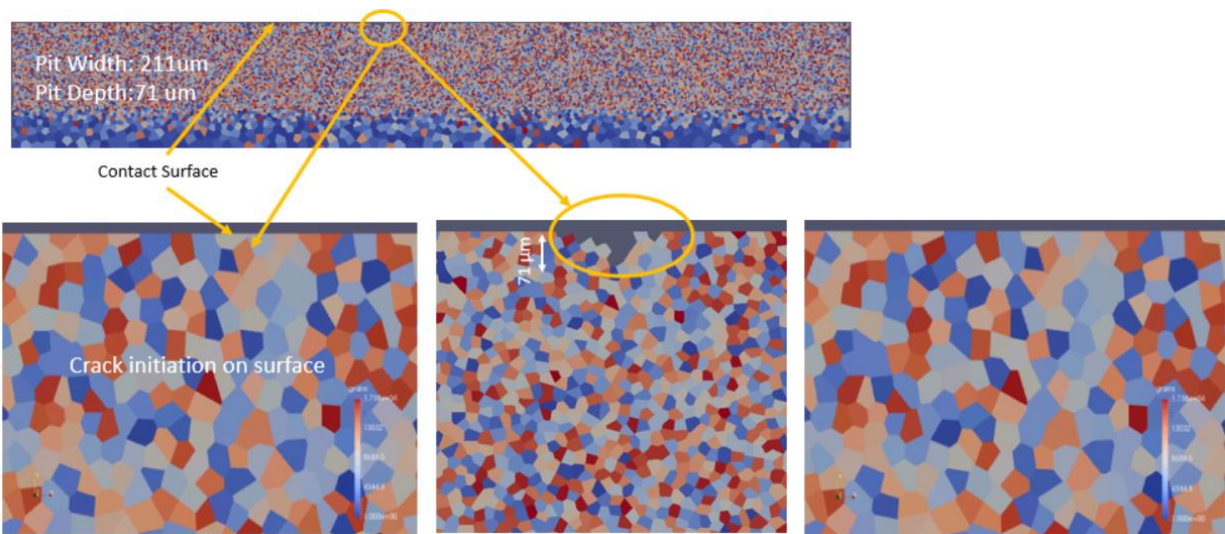


Figure 24. Damage in material domain showing crack initiating on the surface and resulting removal of material causing a surface damage of 71 µm depth

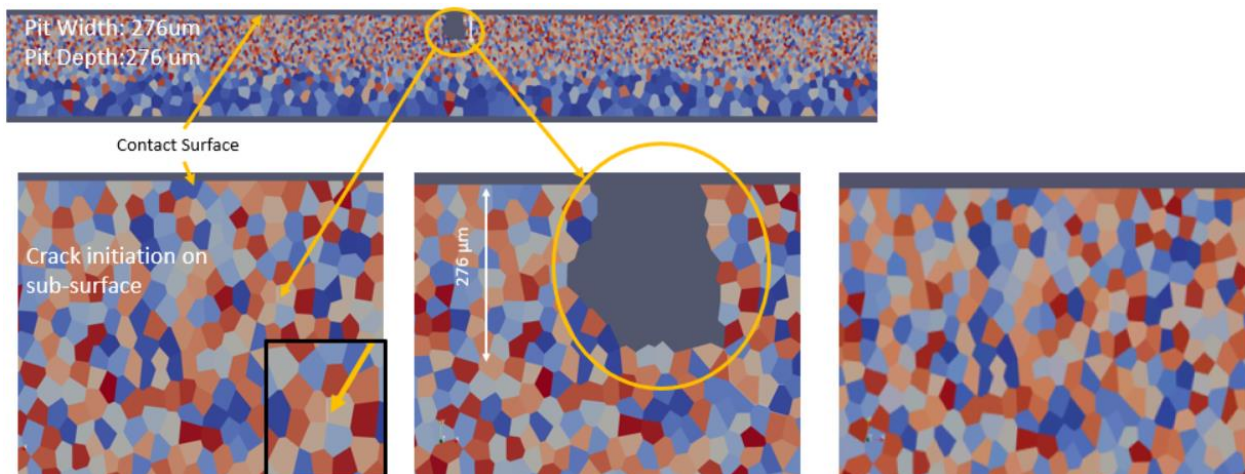


Figure 25. Damage in material domain showing crack initiating in the subsurface and resulting removal of material causing a damage of 276 µm depth

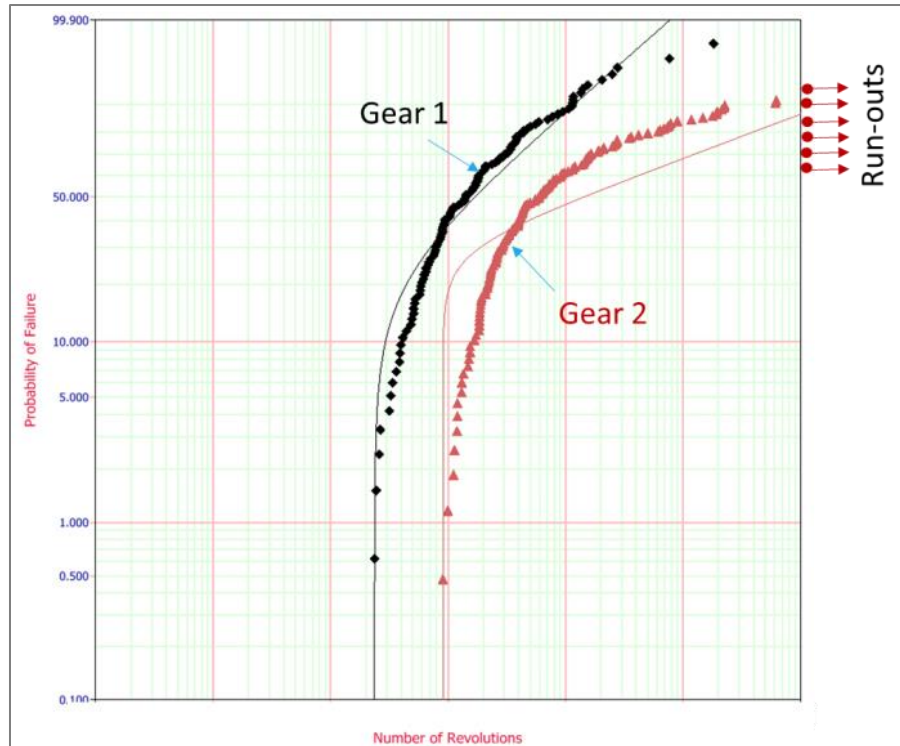


Figure 26. Comparison of life distribution of Gear 1 and Gear 2.

4.3.3 Optimization Module

The overall goal of the project is to help aid in exploring how models can be combined to aid in business decisions. The framework presented in this report discusses how submodels can be combined into one large overall model with the inputs being design requirements and usage information, and the outputs being the life-cycle and total cost. Using the large overall model, an optimization model can be developed. The optimization model can be formulated to solve two separate business problems. First, the problem of minimizing cost while maintaining a desired life-cycle, and second, the problem of maximizing the life-cycle while maintaining a desired cost.

Due to the high complexity of the search space, a genetic search algorithm method was chosen to implement the optimization. The process of genetic search can be seen in Figure 27. First, a population of options is generated. Then all the options generated are evaluated based on some criteria (e.g., life-cycle and cost), and then the best options are selected. The best options are randomly combined together to generate new options for the next generation of the genetic search. Sometimes, the next generation has small mutations to help prevent local minima or maxima in the search. The new generation is then evaluated and the best options are selected again. This process continues until the desired goal is reached based on user-defined success criteria or a sufficient number of generations have passed.

The generic search algorithm for the life-cycle and cost tradeoff model works by generating many random inputs (surface roughness, stress, speed, etc) within the boundaries of each input, which are set by the user. Each random guess is put through the framework to assess the life and cost of the option. The life and cost are outputted and compared to the desired requirements. For example, Table 4 demonstrates some randomly generated options. The goal of the optimization problem for Table 4 is to minimize cost while maintaining a life of at least 20. No option with a life prediction below 20 will be

Table 4. Genetic search algorithm population with a required life of 20.

Guess	Surface Roughness	Stress	Speed	...	Life Prediction	Cost Prediction	Percentage
1	20.11	114.14	3.13	—	17.7652	7184.462	Not Included
2	11.24	121.07	8.24	—	88.75594	11213.21	9.99%
3	38.02	103	5.43	—	14.71042	21264.21	Not Included
4	14.78	112.39	5.21	—	39.61786	8654.457	7.71%
5	19.15	121.24	8.11	—	51.34498	18829.36	16.78%
6	27.1	100.79	2.97	—	11.04599	8112.285	Not Included
7	36.89	119.32	4.31	—	13.94061	18971.39	Not Included
8	15.52	121.12	8.88	—	69.30062	16692.47	14.88%
9	30.04	100.43	0.42	—	1.404148	1267.105	Not Included
...	...	...	...	...	...	...	...

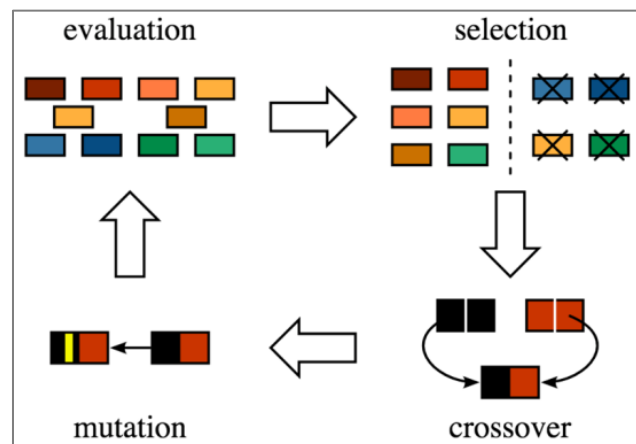


Figure 27. Genetic search algorithm process.

selected for the next generation of the genetic search. The options with life above 20 were selected as parents of the future generation at a higher rate if their cost is lower (this can be seen in the percentage column of Table 4).

Then two of the life-greater-than-20 options were randomly selected. These two options serve as the parents of an option in the next generation. A new option is generated by randomly selecting inputs from either of the parents. The new option with the random combination of inputs from the parents will serve as one option for the next population, and this process is repeated until the number of options in the next generation is equal to the population of the previous generation.

After the next generation is generated, each option is re-evaluated by the framework to get a life and cost. As the generations grow, lower cost options meeting the minimum life of 20 parent more options because of lower cost, and the higher cost options have fewer children. This causes the genetic search algorithm to converge to lower cost option while maintaining the desired life.

4.3.4 Wrapper and Knowledge Conversion Module

A graphical user interface (GUI) was developed for the optimization systems the team created in different systems and formats, and then merged into one single point wrapper for users to input Cost, Life, and Manufacturing data and receive estimated outputs corresponded to each use case scenario. The wrapper has three different sections for each use case, and also has two different charts/data visualizations:

1. Users start by selecting their use case and are redirected to the corresponding system (Life and Cost, Design for specific life, service, and Repair).
2. From there the user can see the guides for each input variable in the tooltip sections as well as the suggested maximum values and input ranges. The system is easily customizable and has minimum implementation process and server configuration and setup.
3. After submitting each use case, the system communicates with Life, Cost, and Manufacturing models via API and returns the corresponding outputs.

Since the wrapper provides a single data point output (for each scenario the user inputs), a data visualization system was developed using Tableau Software² to give the user ability to compare their returned value to all other possible values that they could have. From the visualization dashboards users can test different what-if scenarios and trade-off studies. Users can find the correlations between the input variables in Life, Cost, and Manufacturing processes and understand how increasing/decreasing one would affect the objective functions.

In designing the final product, several iterations and discussions on the wrapper and the communication network occurred between Boeing and the other data integrators, before the final version was settled upon. Figure 28 shows the communication network for the system. Georgia Tech created the manufacturing assembly to feed communication link. Sentient Science provided inputs, the reliability model outputs, and worked with Boeing and Penn State on GUI interface data format for distribution network to create four models – Cost, Performance, Reliability/Life, and Manufacturing Inspection. Boeing then next began looking at the integration in different platforms and in different languages to

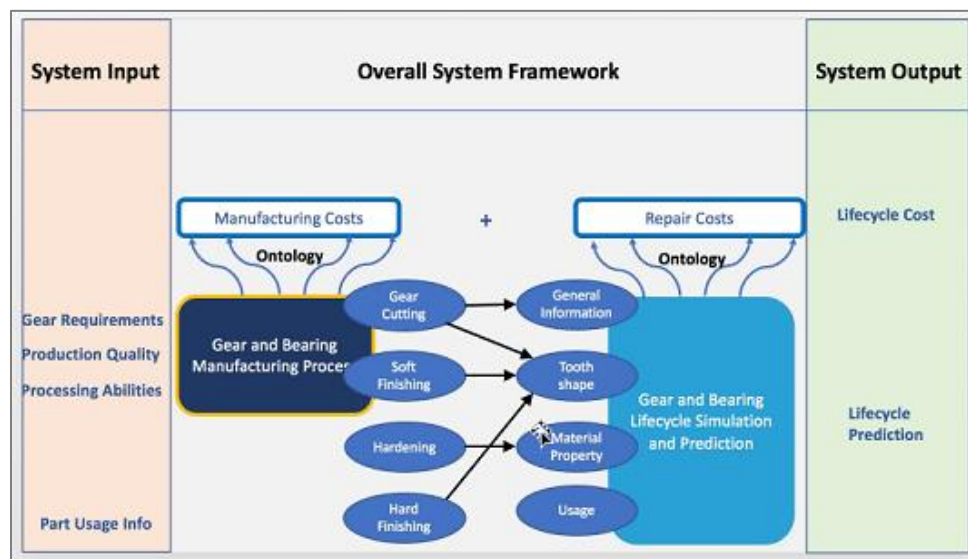


Figure 28. Overall system framework: network communication.

² Tableau Software is a registered trademark of Tableau Software, Inc.

best optimize the delivery of data and ease of use for updates. The design took shape with Penn State driving the backbone and Boeing connecting the infrastructure.

The flow chart depicted in Figure 29 shows the integration modules and effort to wrap the data from the teams and present a consolidated view for the use to query. As the breadth of the template grew, life-cycle estimation and cost data for each query through simulation exercises were added.

Figure 30 and Figure 31 show the input screens and their information is given in the following list:

- **Input** – Manufacturing data
- **Process** – Select the gear process for which you want to build scenarios
- The basic framework of the wrapper included the integration of the team models with a GUI interface that included the following:
 - Usage – speed, torque, misalignment, center distance, axial offset
 - Cost – unit cost, operational and spare units, operational units produced, spare units produced, usage hours per month, replacement time, shop visit cost, cost escalation rate per year
 - Gear Details – gear type, gear outer diameter, face width, material, material hardness, desired profile accuracy, raw material shape, gear module

The output gives the results for total residual stress, surface roughness and total cost for each pair of relationships (Figure 32). From this iterative process Boeing worked with simulations to guide the updates in a logical manner, and refining the wrapper during the development process.

Since the studies were done based on a limited number of samples that were tested and analyzed by Sentient Science, more data points were needed to perform sensitivity analysis and trade-off studies. Boeing used statistical simulation models from Sentience Science as well as Genetic Algorithm (Machine Learning) model from Penn State to generate more data points with the defined characteristics. Boeing then used those additional data points to create the Sensitivity Analysis dashboards.

Visual Dashboard features and attributes are the following:

- Misalignment versus Cost and Life
- Torque versus Cost and Life
- Surface Roughness versus Cost and Life
- Residual Stress versus Cost and Life

The dashboard allows the user to look at cost versus life tradeoffs model, and helps the user to perform a Sensitivity Analysis for each given parameters. It helps answers questions per the input selected if a certain total cost is given:

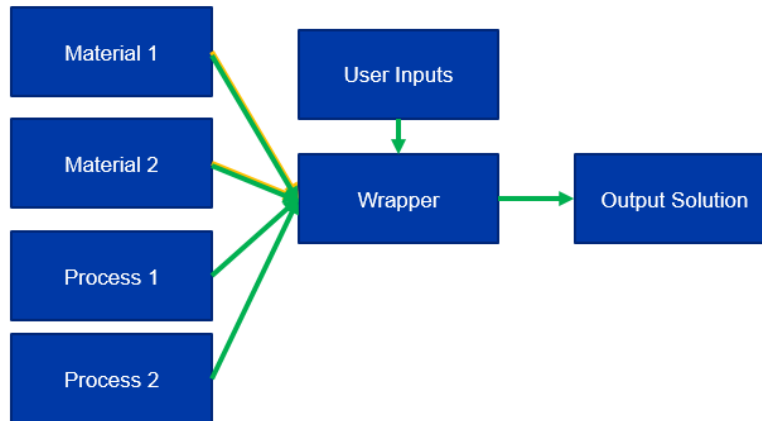
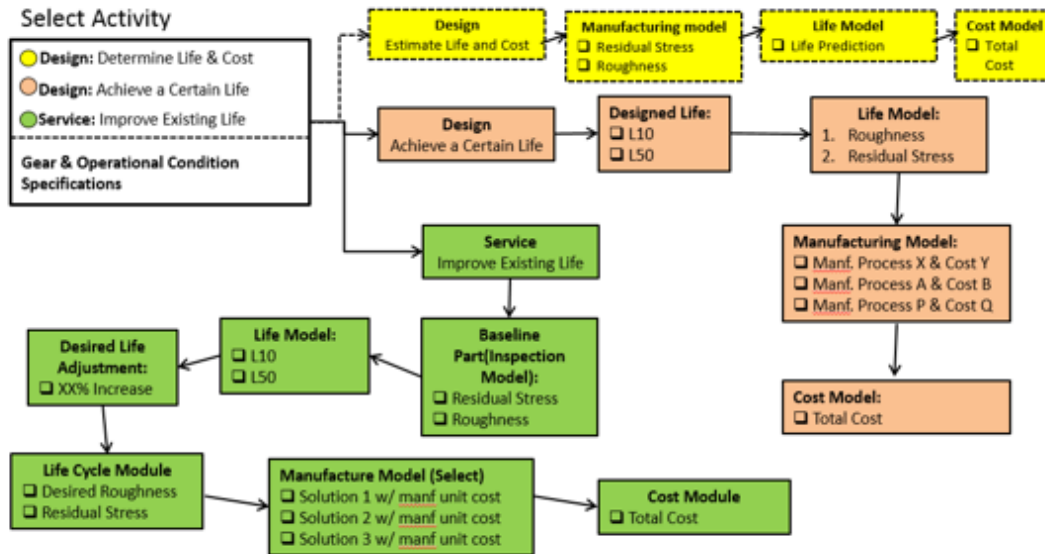
- What is the maximum lifespan and what can be anticipated with different attributes selected?
- If there is a particular life or a range for life the user wants to attain: What is the total cost one can anticipate? What manufacturing attributes (from the manufacturing model) will you need?).

These attributes include the opportunity to look at life-cycle estimates and impacts to repair costs versus scrap value of the part.

The user has a visual opportunity to select and build a variety of trade for each of the attributes in a collective manner.

Using the dashboards, users can define an acceptable range for variables such as Manufacturing Cost or L10 Life and see what options for Residual Stress, Surface Roughness, Misalignment, and Torque are

Use Cases



Options	Material & Manufacturing Options						Product Desire Options		
	Gear Raw Material	Gear Cutting Methods	Soft Finishing	Hardening	Hard Finishing	Desired Part For Products	Service Duration	Working Condition	Production Cost
1	Material 1	Gear Hobbing	Gear Shaving	Carburizing	Gear Grinding				
2	Material 2	Gear Shaping	Finish Rolling	Nitriding	Skiving				
3		Gear Broaching	Cermet Hobbing	Carbonitriding	Hard Shaving				
4		Gear Rolling		Flame Hardening	Hard Gear Honing				
Gear Set 1	Material 1	Gear Hobbing	Gear Shaving	Carburizing		Completed	3		\$\$\$
Gear Set 2	Material 2	Gear Hobbing		Carburizing	Gear Grinding	Completed	5		\$\$\$\$

Figure 29. Flowchart depicting integration of modules.

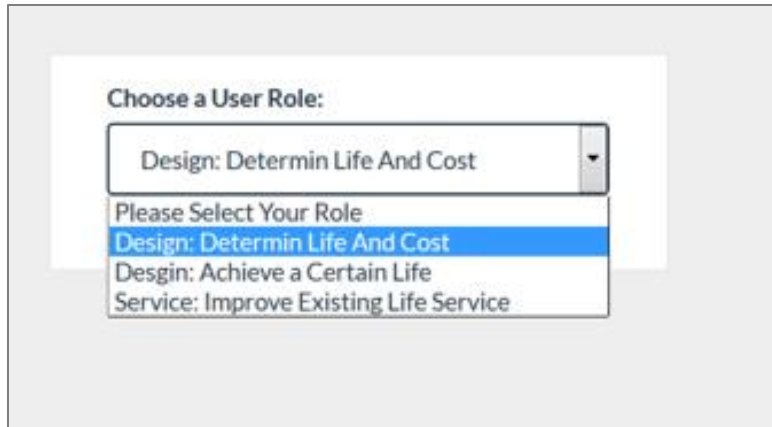


Figure 30. Opening screen.

DMDII Roles		Design: Determin Life and Cost	
Gear Type:	Sun	Speed:	65.9
Gear Outer Diameter:	600	Torque:	85
Face width:	220	Misalignment:	0.08
Material:	Steel	Center Distance:	9
Material hardness:	41	Axial offset:	0.002
Raw Material Shape:	Cylindrical	Unit Cost:	6.4
Process:	☐ Gear Cutting:Hobbing->Hardening:Nitriding->Hard Finishing:Grinding ☒ Gear Cutting:Hobbing->Soft Finishing:Shaving->Hardening:Nitriding ☐ Gear Cutting:Hobbing->Soft Finishing:Shaving->Hard Finishing:Grinding	Operational and Spare Units:	2130
		Operational Units Produced:	2100
		Spare Units Produced:	2000
		Usage Hours per Month:	90
		Replacement Time:	250

Figure 31. Input screen.

DMDII Roles		Design: Determin Life and Cost	
Raw Material Shape:	Cylindrical	Replacement Time:	250
Gear Module:	18	Shop Visit Cost:	17
		Cost Escalation Rate per year:	5.3
2:Process:	soft finishing		
Process:	shaving		
Time:	10		
3:Process type:	hard finishing		
Process:	grinding		

Total Residual Stress: 40
 Surface Roughness: 20
 Lambda: 9
 K: 5
 Total Cost: 52421

OK

Figure 32. Output screen.

available. Users can perform this sensitivity analysis for Manufacturing Cost, L10 Life, and Reliability costs and see which factors (Residual Stress, Surface Roughness, Misalignment, and Torque) are more significant and will have highest impact in cost and/or life. These dashboards can be used as a tool for DFM practices to minimize manufacturing cost and increase life of the parts.

4.3.5 Cost Module

Rolls-Royce used a proprietary total life-cycle cost model to model the year-to-year costs of producing and maintaining a fleet of a units. Rolls-Royce uses the model for its Defense fleets, but in this case it was retrofitted to model a fleet of John Deere gear systems. The capabilities of this model are Life-cycle Cost and Logistics planning.

The main inputs used in the fleet cost included the following:

- Gear unit cost
- Gear fleet size
- Inflation rate
- Gear replacement cost
- Weibull statistics: strength and slope obtained from the Sentient Science life model
- Current/spare units
- Yearly delivery schedule
- Manufacturing cost
- Usage data (cycles/year)
- Replacement time
- Shop visit costs
- Cost escalation
- Service action (sentencing) during inspection post service

The primary outputs were:

- Average time between part removal (mean time between removal)
- Number of removals (events) per year
- Annual cost per year

Some of the assumptions were:

- Part supply chain available
- Parts are replaced rather than repaired
- All suppliers cost same

Figure 33 shows the variation of average time between part removal, number of removals per year and the annual cost per year. The numbers have been normalized to protect proprietary cost information.

4.4 Use Cases

The framework is demonstrated using a simple gear system provided by John Deere. The system consists of two gears and associated bearings and shafts. Three use cases are programmed into the simulation:

- **Use Case No. 1. Baseline: Design Scenario** – What is the total cost and life-cycle given the design parameters? One can iterate on the various manufacturing processes, usage parameters (torque



Figure 33. Average time between events, number of events per year and annual cost per year [normalized to protect proprietary information].

and misalignment) and equivalent life-cycle life and costs are obtained. Figure 34 shows the architecture of use case No. 1.

- **Use Case No. 2. Optimization for Design Parameters** – What is the total cost and life-cycle given residual stress and surface roughness parameters? The system performs iterations on the various manufacturing processes and optimized process and equivalent cost and life-cycle prediction is obtained. Figure 35 shows the architecture of use case No. 2.
- **Use Case No. 3. Repair Scenario** – Most complicated of the use cases. A micropitting case study is used here. The gear is assumed to be removed at a lower wear point and a repair process (gear grinding followed by a super finishing process) is conducted on the gear. This repaired gear is then subject to the lifing and cost assessments are made. These are then compared to a baseline of gear replacement cost (essentially two cycles of new gear) to provide a life-cycle assessment. Figure 36 shows the architecture of use case No. 3.

4.5 Modes of Operation

For each of the use cases in Section 4.4, the following paragraphs show the various modes of operation. The model can be used in three different user role modes (Figure 37):

- Design Life and Cost
- Design to Achieve Certain Life
- Improve Existing Life in Service

Each user's role will have its own specific input variables and will communicate to its assigned web API. Figure 38 shows the input variable screen. Once the user inputs her/his parameters, the system will show the output result based on each use case (Figure 39). After that the user can use his/her own built-in dashboards to perform Sensitivity Analysis or Trade-off Study for the specified manufacturing parameters (Figure 40).

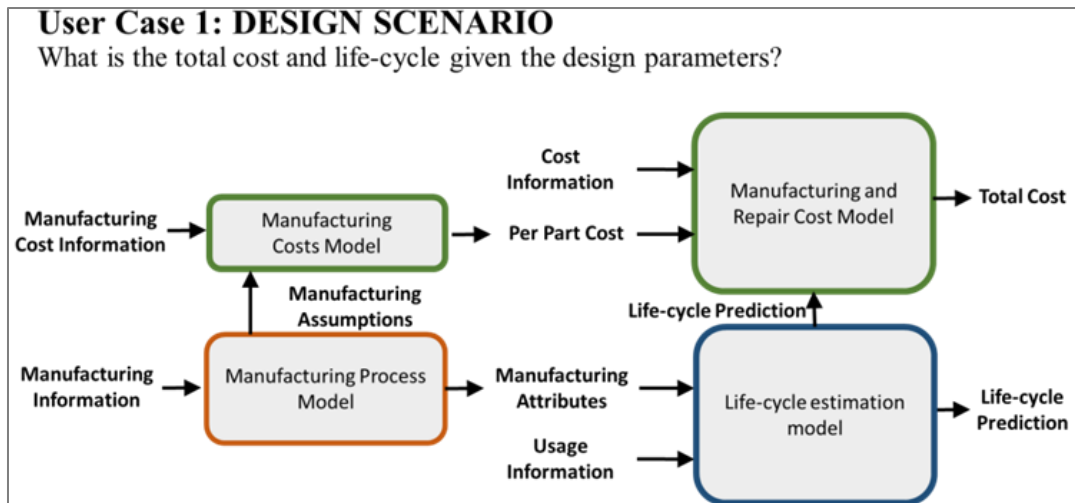


Figure 34. Use Case No.1 – baseline: design scenario.

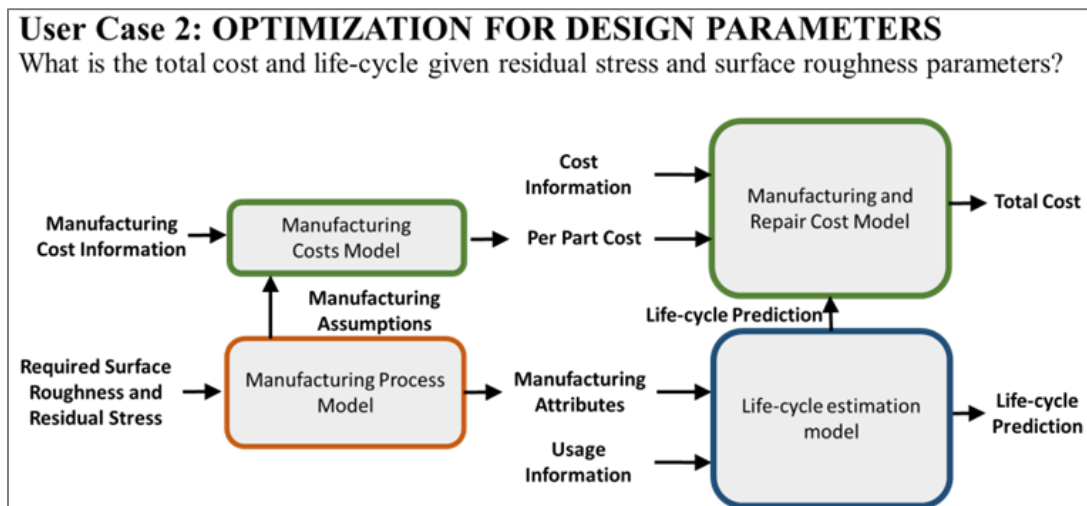


Figure 35. Use Case No. 2 – optimization for design parameters.

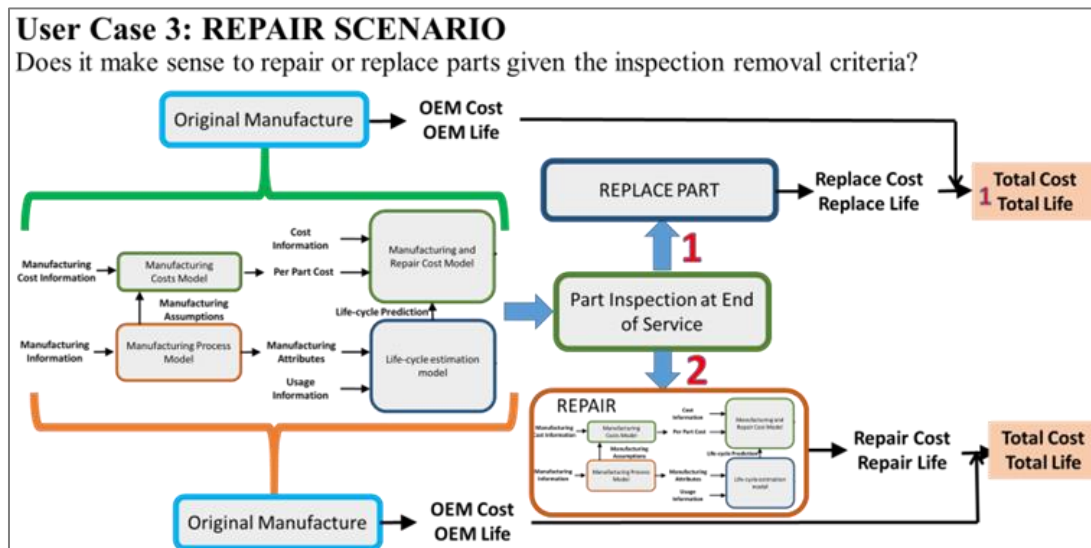


Figure 36. Use Case No. 3 – repair scenario.

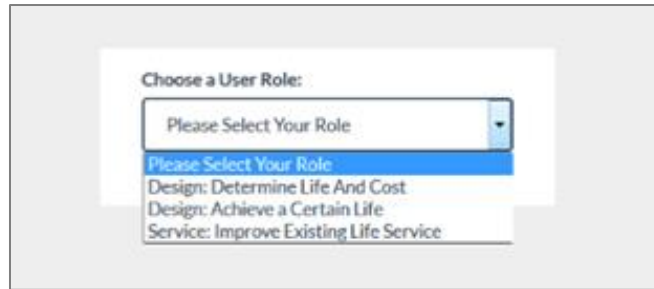


Figure 37. Modes of operation.

Figure 38. Input variable screen.

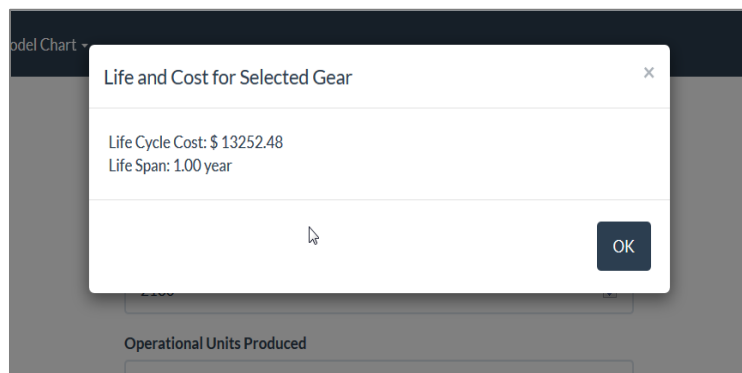


Figure 39. Output screen.



Figure 40. Dashboard sample.

Figure 41 displays a schematic of the information flow within the Manufacturing Model. The objective of the Manufacturing Model is to represent product manufacturing, assembly, and repair knowledge so the product manufacturing sequence selection, life-cycle estimation, cost estimation, and affordability trade-off could be analyzed and optimized. Figure 42 shows an example of how information is transmitted from the wrapper to query the manufacturing knowledge database when conducting a what-if study.

As shown in Figure 42, the desired design inputs are sent to the manufacturing knowledge database via the web interface. Criteria for filtering available manufacturing sequences are listed in the middle, and candidate sequences and their IDs that satisfy the criteria are sent back to the user. The lower part of Figure 42 shows the manufacturing knowledge database outputs the attributes associated with the selected manufacturing sequence back to the user/wrapper, which corresponds to the bottom part of Figure 41.

The Manufacturing Model is also expandable so that:

- Attribute values for each manufacturing sequence represented in the database can be easily updated
- Knowledge framework of the Manufacturing Model can be easily expanded to represent new manufacturing sequences

Figure 43 shows a schematic of the available interactions between the user/wrapper and the Manufacturing Model.

As shown in Figure 43, when the user/wrapper communicates with the Manufacturing Model there are eight types of interactions, as listed in the following:

1. The user/wrapper inputs the desired design/quality parameters to the Manufacturing Model
2. The Model provides available manufacturing sequence options
3. The user selects a manufacturing sequence
4. The Manufacturing Model outputs gear quality and cost data
5. The user/wrapper inputs field data
6. Field data is verified by the Manufacturing Model

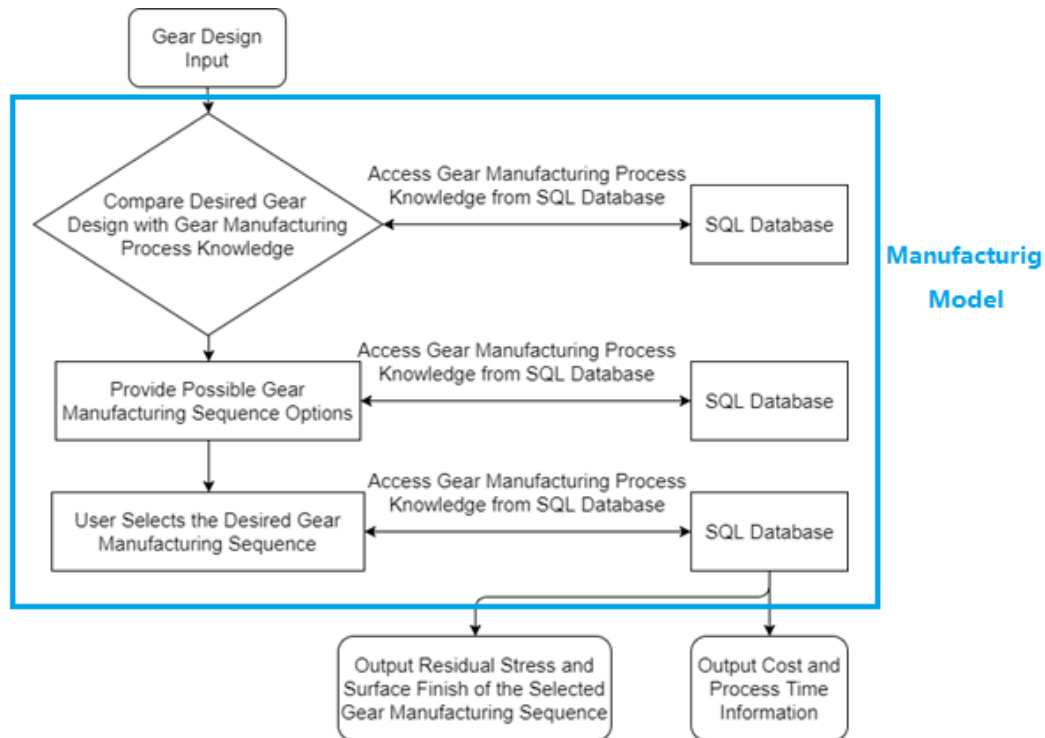


Figure 41. Information flow in the manufacturing model.

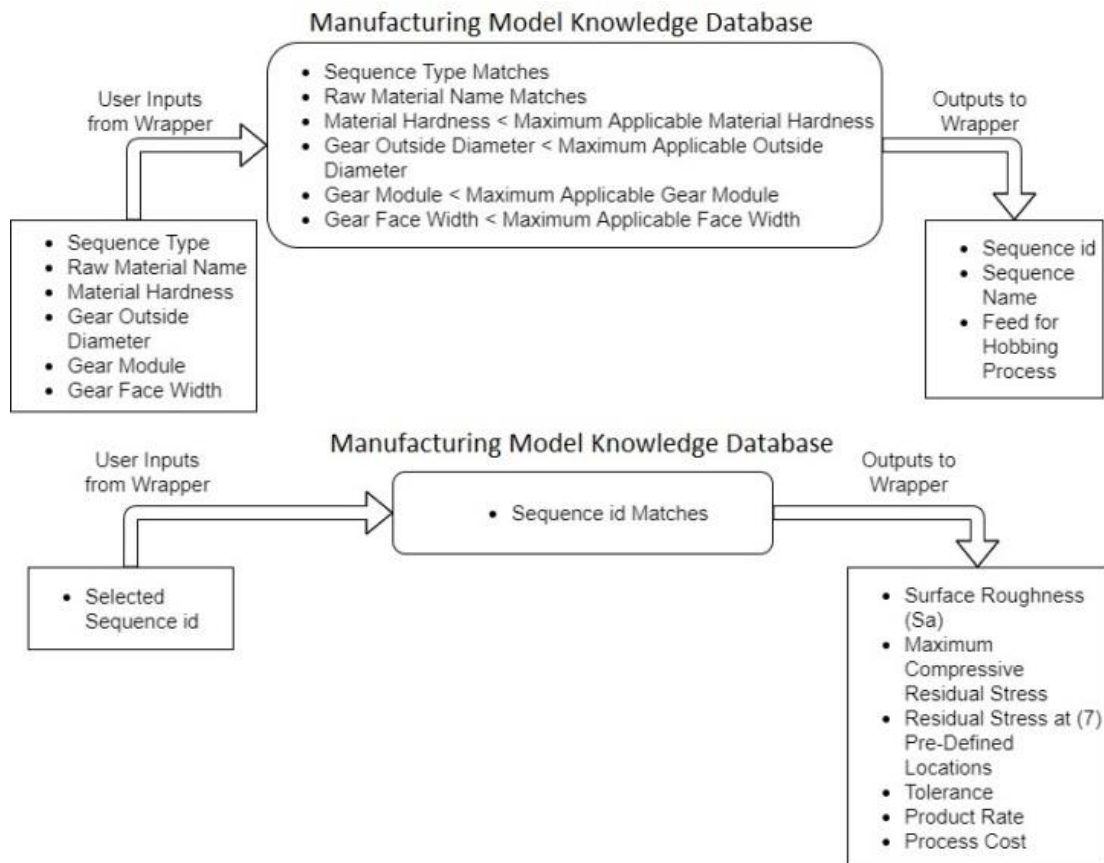


Figure 42. Detailed information flow between wrapper and manufacturing knowledge database.

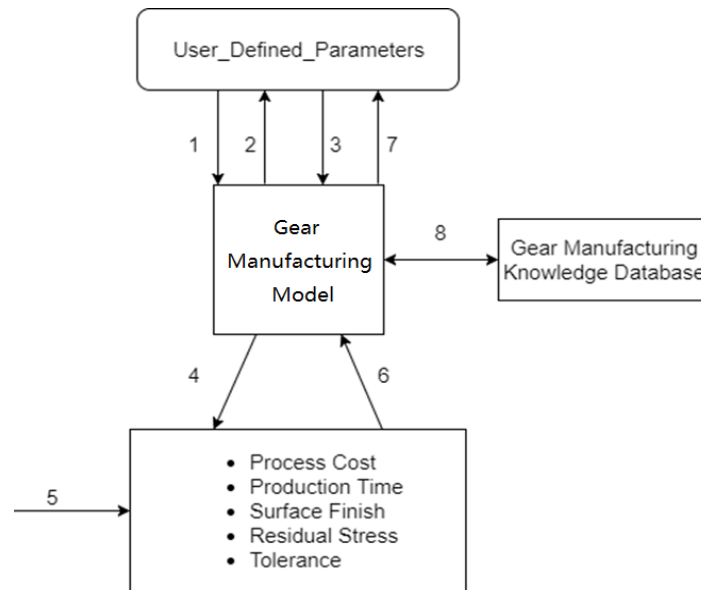


Figure 43. Interactions between the user and the manufacturing model.

7. If field data is considered as an outlier, the Manufacturing Model flags it and provides feedback to user/wrapper
8. Database is updated with verified field data

Examples of how these interactions are achieved have been presented in the other sections of this report. Information transmission between the user and the Manufacturing Model, as indicated by the arrows in Figure 43, is realized via either the web interface or the web-based API.

4.5.1 Sensitivity Studies

Simulations were conducted on the two gears to evaluate baseline conditions, and then sensitivity analysis was performed on one gear by varying the following parameters:

- **Manufacturing Process (changing surface roughness and/or residual stress)**
 - GS1 – Sensitivity 1 - In this case, the effect of superfinishing was analyzed on the life of gear. Keeping all the other parameters constant, the surface roughness of Gear 2 was reduced to reflect a superfinish scenario. The superfinishing process RMS surface roughness value was obtained from the manufacturing model.
 - GS2 – Sensitivity 2 - In this case, an alternative manufacturing process sequence was considered based on outputs of the Manufacturing Model provided by Georgia Tech. In this scenario, the gear was assumed to be superfinished (lower surface roughness) but not shot peened (as machined residual stress profile).
- **Load (applied torque)**
 - GS3 – Sensitivity 3 - Applied torque on the gears was increased by approximately 20% to consider the effect of higher load.
- **Misalignment (assembly misalignment)**
 - GS4 – Sensitivity 4 - In the baseline cases, it was assumed there was no misalignment between the gears. The misalignment was increased to 1 mrad.

The list of baseline and sensitivity studies and the parameters used in the gear demonstration are described in Table 5.

Table 5. List of simulated scenarios.

Test No.	Description	Roughness (mic)	Residual Stress (max comp.)	Torque (Nm)	Misalignment (mrad)
GB2	Gear 2 Baseline	0.5-0.7	RS1	2100	0
GS1	Manf Process Sensitivity 1	0.1-0.3	RS1	2100	0
GS2	Manf Process Sensitivity 2	0.1-0.3	RS3	2100	0
GS3	Load Sensitivity	0.5-0.7	RS1	2500	0
GS4	Misalignment Sensitivity	0.5-0.7	RS1	2100	1
GB1	Gear 1 Baseline	0.8-1.0	RS2	2100	0

4.5.1.1 Manufacturing Process Sensitivity (GS1 and GS2):

A comparison of manufacturing processes with the baseline Gear 2(GB2) was conducted using the values in Table 3. Figure 44 shows the comparison of life distribution of manufacturing process sensitivity scenarios with baseline. From Figure 44, the following observations can be made:

- Superfinishing results in increase in L10 life of Gear 2. This is most likely due to reduced asperity contact, which results in reduced friction and reduced contact pressure spikes.
- Superfinishing along with shot-peening increases L10 life of Gear 2 even further. This is due to the added effect of compressive residual stress. Higher compressive residual stress plays a role in limiting damage propagation.
- This analysis demonstrates alternative manufacturing processes can be analyzed using DigitalClone technology to evaluate their impact on component life or reliability.

4.5.1.2 Load and Misalignment Sensitivity (GS3 and GS4)

The torque is increased by 20% from the baseline and the misalignment is increased to 1 mrad from 0 mrad. All other parameters are kept constant – the same as Gear 2 baseline (GB2). Increasing torque and misalignment resulted in increase of contact pressure and therefore contributed towards reduction in life as compared to the baseline case. This is illustrated in Figure 45.

This analysis demonstrates the impact of assembling or operating conditions on component life. The change in life or reliability of a component resulting from uprating or downrating a gear set or using the same design in a different application (with different loads) can be evaluated using DigitalClone technology.

Sentient Science used the DigitalClone technology to compare component life of two gears provided by John Deere and conducted a sensitivity study over manufacturing processes and operating conditions. The DigitalClone technology provides estimates of component life or reliability in a shorter time as compared to conventional testing methods. As a result, several different manufacturing, design, supplier, operation, or repair options can be evaluated in reduced time and cost while integrating with other models in the framework, such as the manufacturing model that provides inputs to the life/reliability model and cost model, which uses the inputs of the life model. Table 6 summarizes the different scenarios simulated in this project and the resulting component life or reliability estimates.

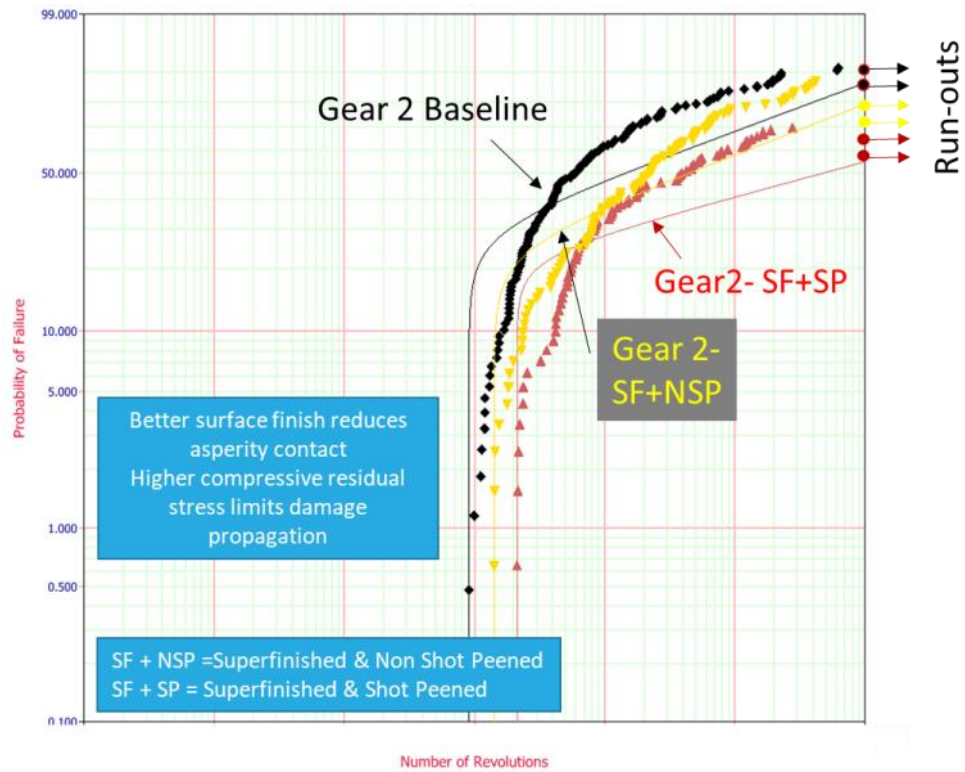


Figure 44. Comparison of life distribution of manufacturing process sensitivity scenarios with baseline.

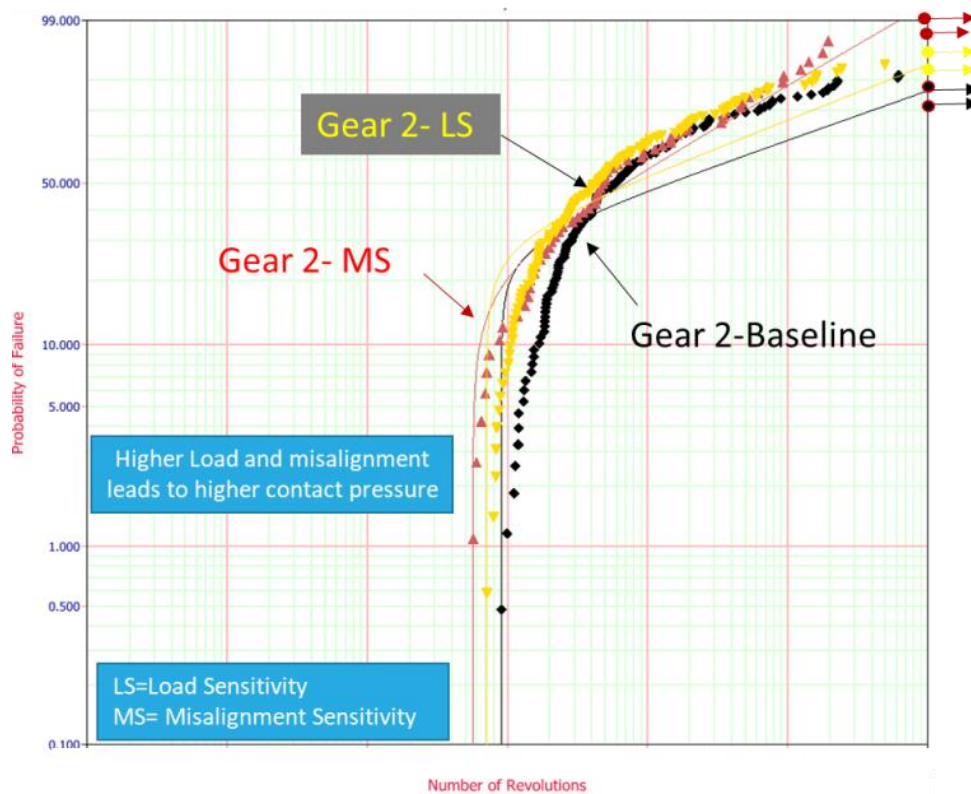


Figure 45. Comparison of life distribution of load and misalignment sensitivity scenario with baseline.

Table 6. Summary of all scenarios and resulting life distribution parameters calculated by DigitalClone technology (anonymized as per requirement of John Deere).

S No.	Description	Roughness (mic)	Residual Stress (max comp.)	Torque (Nm)	Misalignment (mrad)	Weibull Strength	Weibull Slope	Weibull Location	L10 Life	L10 Life Factor
GB2	Gear 2 Baseline	0.5-0.7	RS1	2100	0	2.95E+11	0.25	9.05E+06	4.56E+07	1
GS1	Manf Process Sensitivity	0.1-0.3	RS1	2100	0	2.01E+13	0.18	2.12E+07	1.07E+08	2.3
GS2	Manf Process Sensitivity	0.1-0.3	RS3	2100	0	3.17E+11	0.26	1.42E+07	7.26E+07	1.6
GS3	Load Sensitivity	0.5-0.7	RS1	2500	0	9.02E+10	0.28	7.13E+06	3.61E+07	0.8
GS4	Misalignment Sensitivity	0.5-0.7	RS1	2100	1	5.98E+09	0.41	5.67E+06	3.17E+07	0.7
GB1	Gear 1 Baseline	0.8-1.0	RS2	2100	0	5.98E+08	0.58	2.37E+06	1.47E+07	0.3

V. ACCESSING THE TECHNOLOGY

The developed framework is generic and can be shared within the DMDII community. The framework is pervasive and can be applied to almost all part types in a wide variety of products. It had been designed to be system agnostic even though specific tools are used within the program for the purpose of demonstration of the concept.

The items provided by members, who have background IP, are the following:

- DigitalClone lifing modeling tool from Sentient Science
- Gear/bearing sets with their associated characteristics and operating conditions are owned by John Deere
- Cost modeling tool is owned by Rolls-Royce Corporation
- The Tableau visualization tool is commercially available and requires purchasing of software license

Figure 46 shows the method to link the various modules within the framework and contact information for the individual owners.

The organizations can implement the resulting framework into their product and processing system environment with similar modeling tools with their own specific parts. There is no specific system requirement because it completely depends on the scope and the detail level involved in the application. For the digital feedback channel, it does depend on the network capability of the organization to allow users access to the system output.

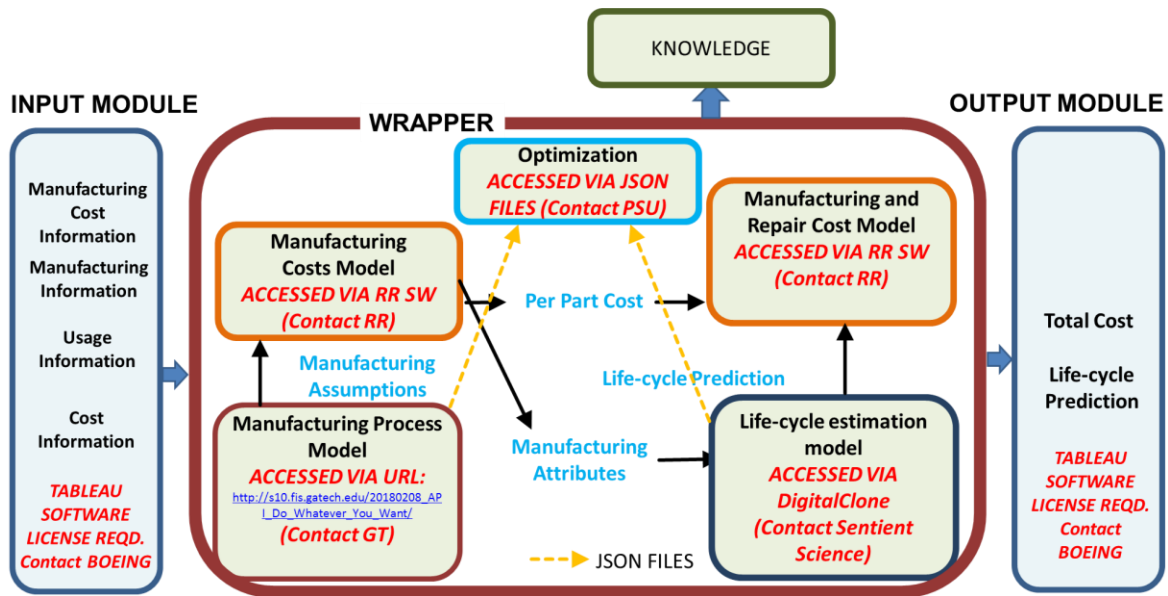


Figure 46. Framework modules, links (black and yellow arrows), contacts (red).

5.1 Innovation

The current design and life-cycle management methodology is very expensive. It involves many trial-and-error iterations, drives a lot of constant change, and tremendously increases the cost of sustainment. Current tools assume each component will meet their individual design intent as long as variability is within the tolerance or assembly stack limits. The current design culture mainly focuses on individual parts and features but lacks consideration from a holistic system/subsystem level in the context of variability management and its impact on cost/performance. Lifting, performance, and life-cycle cost are directly associated with how the parts actually interact with each other. Simply optimizing piece part design only partially addresses the overall issue. The digital framework will spearhead the resolution of this limitation.

While there are no parts manufactured exactly on nominal, maximum, or minimum of the tolerance limits, taking into account of both as-built and as-used part/system data provides more realistic and valuable feedback information for product improvement. The design tools also have very limited or no capacity to support real-time automated or semi-automated knowledge transfer from the other life-cycle stages for decision making in life-cycle considerations.

The project provides a generic digital framework for an advanced systems architecture enabling new technologies and models to be integrated within an OEM's feedback loop. The structured platform for data and knowledge sharing that this project has developed avoids the mentality of single-use data, which is prevalent in many organizations today. Currently, data are commonly distributed to or accessible only by specific parties in an organization. However, this project has created an open environment for sharing that allows users to create connections and identify relationships across the supply chain that will drive changes to optimize the various -ilities under consideration.

The DigitalClone model simulates material performance at the microstructure level, allowing for accurate calculation of fault initiation and small crack growth by accounting for items such as surface finish, lubricant, material quality, and material microstructure. The model's ability to predict crack initiation within the material microstructure gives the earliest warning to future failures and more accurate imminent failure identification.

Finally, the project has developed a knowledge base of guidelines and training for future use by academia and industry to improve their communication of product definition throughout the supply chain. This project approached the issues of improvements in various -ilities and knowledge sharing by developing a common platform that could be broadly applied throughout industry. The tools and processes developed during this project are available for use by the DMDII community per contractual terms therein.

The primary points of contact for the various models are as shown in Figure 46 and given in Table 7.

VI. INDUSTRY IMPACT & POTENTIAL

The developed framework can be applied to a wide variety of industry and mechanical part types that have certain service life. An ordinary gear set was used in this program, nevertheless the methodology can be used in almost any other parts and subsystems. Users will need to populate the system with their data and knowledge tailored to their specific part characteristics, the associated manufacturing processes, the lifing performance model, and the data format converter. The system can also be implemented from a simple and preliminary manner and then progress all the way to in-depth and broad-processing of variables.

Any mechanical design of parts and/or subsystems requiring optimization between the manufacturing cost and part performance (in terms of lifing) can take advantage of the resulting framework. It not only can be applied to designing new parts, it can also be used for making repair/replace decisions at the Maintenance, Repair, and Overhaul (MRO) phase of the product.

Traditionally, lifing and cost assessment are independent processes taking place after the mechanical design is almost complete. During repair and overhaul, the repair versus replace decision has been mainly relying on subjective judgement based on the limited measurement and repair cost analysis. The framework and methodology developed in this program enables simultaneous engineering that takes lifing and cost into account at the critical design stage in both the new and repair phase during the product life-cycle.

Table 7. Primary points of contact for the various models.

Model	Point of Contact and Method
Wrapper	Boeing
Manufacturing Process Model	Georgia Institute of Technology http://s10.fis.gatech.edu/DMII_GeorgiaTech_Demo_Homepage_VF.php#
Life Cycle Estimation Model	Sentient Science accessed via DigitalClone
Manufacturing And Repair Cost Model	Rolls-Royce accessed via proprietary cost model
Optimization Model	Pennsylvania State University accessed via JSON files
Gear System Model	John Deere

The Manufacturing Knowledge framework (or Model) developed and demonstrated in this project is generic and can be tailored to represent other manufacturing process knowledge. It serves as a template for the development of more robust manufacturing process knowledge databases. Future extensions of this framework should consider linking the appropriate attribute fields associated with the manufacturing knowledge with either (empirical or physics-based) manufacturing process modeling and manufacturing cost-estimation software used by industry and/or with data collected through factory information systems (e.g., through MT-CONNECT). This will allow the knowledge stored in the database to be current and relevant to the manufacturers' production operations, thereby serving as a knowledge repository that grows and matures with time.

Industry implications for the DMDII product include the opportunity for visual what-if scenarios in a GUI that is easy to use and gives the end user the opportunity to combine traditional silo information into one visual screen. Decision tools used in industry require multiple sources and our team decision to work with an ontology to build the relationships and further mature this backbone as a baseline for the wrapper design has significant implications not only as a robust decision tool but to give the user the opportunity to scale the options for the variables selected. It also provides the visuality to see the implications of the decision the end user requests in real-time from the unique data collection process. This, combined with the manufacturing process (which also influences the decision), gives the end user a more robust and enhanced product.

VII. TECH TRANSITION PLAN & COMMERCIALIZATION

This final report lays out the detail of the system objective and architecture by using a generic gear/bearing set. Since the framework is generic, future users can retrofit the concept in their own operation, which may have lower levels of readiness of technologies required in this architecture. For instance, they may have different toolsets for the detailed material-based lifing prediction model or the in-depth manufacturing cost model. Certain development should be needed to be conducted based on their product and processes. Nevertheless, the system could be based on their existing capability and then progressively developed into more advanced and accurate levels.

The deliverable from this program is a system framework and methodology, not a directly implementable piece of equipment, hardware, or software tool for a specific application. The commercialization should be in the form of engineering consultation, system design, and optimization. System developers and software vendors could employ the developed concept into their own products for the applications with which they deal.

Refer to Section V for details on how the system demonstrator model can be accessed and used.

VIII. WORKFORCE DEVELOPMENT

The DMDII facility at Goose Island and university and industry partners will be able to take advantage of the outcome of this program and enhance their training curricula. Sharing the generalized development results and lessons learned from this program will benefit U.S. industry, both large OEMs and subject matter experts (SMEs), and academia.

Within the various OEMs, this project will enable improved interoperability and communications among business units. The result can improve the responsiveness and competitiveness of the Department of Defense and industry supply chain; thereby enabling supply chain participants to openly communicate and share information through a standardized platform to more quickly address supply chain issues, to

generate innovative or better approaches to design and manufacturing, and to perform data analysis to predict and address trends across a product line or supply chain.

The concept developed in this program should be a critical element for the next generation of system engineering because it can help companies incorporate the various -ilities (reliability, affordability, serviceability, etc) at the design phase in a systematic manner and not as an afterthought. This should help the industry to move away from the current sequential style of practice so that they can have shorter design-make cycle time with improved performance.

IX. CONCLUSIONS/RECOMMENDATIONS

A high fidelity network system simulating the individual life-cycle stage (such as design, manufacturing, test, operations, etc) along with data and a knowledge converter module wrapped into a system framework that has been exercised as required to enable optimization has been developed. The individual models incorporate process and data information relevant to the specific attribute/life-cycle stage. The data output from this simulation system is then converted into actionable knowledge to make decisions to improve design, manufacture, inspection, and assembly and to optimize the various interdependent -ility topics (e.g., system reliability, affordability) under consideration. The effort also focused on gap analysis and the design of possible paths to bridge the gaps instead of addressing the procedural mechanics or the development of automated translators. It can be easily updated and expanded to represent more process methodologies.

For the gear demonstrator model, the manufacturing knowledge data could be further expanded. Additional manufacturing process sequences for manufacturing other products should be included to enhance the model's comprehensiveness. In addition, due to time limitation, the current implementation of the knowledge database only considers manufacturing sequences at the sequence level but does not include knowledge pertaining to each process in the sequence. The accuracy of the model could be further improved if each manufacturing sequence includes details of each manufacturing process within it. Physics-based models for determining the relationships between some of the attributes could be included to improve the accuracy of the model. For example, a physics-based model capable of predicting the residual stress generated in the workpiece surface as a function of the process parameters could be linked to the database. Similarly, manufacturing process cost estimation models/software used in industry to estimate unit manufacturing cost could be linked to the unit process attribute contained in the current implementation. Finally, as noted earlier, certain process attributes in the database could be computed from actual manufacturing process inspection data collected using factory information system.

The architecture built was the first step to begin building further integration and attributes in a dynamic environment and create the feedback loops to the company enterprise systems and company full life-cycle. Adding in AI and machine learning to the architecture would also bring value to the deliverable. One key element making the wrapper stand out from traditional products is the combination of silo information (materials, cost performance, etc) built with the manufacturing processes, thereby giving the next dimension of knowledge to the end user. Not only are the options selected but they are also built with the manufacturing process to enhance the knowledge for the end user.

For the demonstration, only a few design and usage parameters were chosen. These could be enhanced by incorporating model-based definition of part features, increased depth into material modeling, incorporation of process modeling of the manufacturing processes, which commonly impact the part

material behavior, and properties resulted from the variety of processes (e.g., heat treat, machining feed/speed, surface preparation, residual stress, etc).

More extensive knowledge sharing in the GUI (e.g., in the Tableau environment) can be incorporated along with improved robustness of the Genetic Algorithm based optimization or can incorporate different types of optimization algorithm.

During complex what-if trade-off studies, a human usually has limited capability to handle more than three to four simultaneous variables without using capable tools. Three-dimensional response surface plots and Microsoft Excel^{®3} based sensitivity study plots have been broadly employed. Yet, such as demonstrated in this project, visualization tools, such as Tableau, can enable the user to interactively study the impact by varying more than one variable simultaneously. This type of tool is necessary for an effective assessment of the sensitivity of the system behavior. This is particularly true when more complex lifing and/or manufacturing models are involved. In this program, it has been discussed that the manufacturing process directly impacts the surface finish and near surface residual stress, which have direct effect on part life from a macro point of view. For improved accuracy, the material microstructure resulting from the forming, heat treat, machining, and surface preparation processes should be incorporated in both the manufacturing process model and the lifing model.

Automated decision making is an ultimate goal. Nevertheless, the degree of automation should be carefully and methodically developed in a progressive manner. Human decision making should not be completely out of loop when dealing with a complex system. Software can be utilized or developed to automatically extract and present all relevant knowledge/information/data to the decision maker. The logic and assumption used in the decision can be automatically recorded so that it can become part of the lessons learned in future reference material

The nature of the lifing and cost models is analytical and numerical once the input conditions are given, yet the manufacturing model has involved a lot of discrete factors, such as shot peen or not, superfinishing or not, different assembly approaches, etc. The current commercial off-the shelf (COTS) optimization tools are not effective for directly handling scenarios with a combination of analytical and discrete elements. Certain software with desirable logics needs to be developed to deal with the discrete conditions and then iterate with the analytic models, such as in the iSight[®] environment.

X. LESSONS LEARNED

The project provided an excellent opportunity for the team members to create the fundamental elements of the digital thread necessary to link design, manufacturing, reliability, and cost models. While considerable progress was made by the team, significant work remains to mature the various models and threads developed in this project. Overall, the program was managed quite well (under budget and on time) and there was good coordination of the team members. Reviews were held on time and involved DMDII, all the team members, and the community at large. The final demonstration at Goose Island in March 2018 during the Tech Showcase was well received by the community as a whole.

Some of the key lessons learned:

- To enhance the usefulness of the system, **the next step would be to create a system accommodating multiple variables and processes.** The template being flexible can accommodate this; we would just need to test more than what was conducted for the

³ Excel is a registered trademark of Microsoft Corporation

demonstration. If we had more time, we could have collected and tested more data to see the patterns and do any adjustments.

- We also could have investigated **how to build in the “dynamic” collection of data**. Sustainability was a solid example to show the overall life-cycle implications to the data from the models we built and the framework for the relationship interaction. This gave the end user not just a single answer but a richer deliverable that not only combined several traditional silos in finance, engineering, and manufacturing but also promoted better decision making. Our sustainability was down further into the project and if we had more time and money, it **would have been nice to test it with other sustainability tasks for the customer and to also test the feedback loops to each of the models for further pattern recognition and enhanced decision opportunities**.
- Integrating different areas of expertise in a digital framework is a difficult problem to solve. In addition to technical expertise of each team, **communal design thinking is very necessary** to exploring the usability, scalability, and applicability of the framework in a real scenario. In this project, the teams had diverse background and their contributions toward this design thinking were commendable. It resulted in discussion of a lot of real challenges and the resolution of some of them within the scope of the project. This helped in highlighting several real problems faced by different departments of an organization. The interaction between the manufacturing, life, and cost models is the key toward creating an optimized product that is both feasible and viable. Put together, these models contribute many more fold when compared to their respective stand-alone use. The life model, for instance, can consider real manufacturing process knowledge, which accounts for the real cost in the manufacturing of a part, which can in turn be used to do trade-off studies with the reliability output of the life model and the output of the cost model.
- However, there are challenges in creating a streamlined data transfer or communication between these models. To resolve some of these challenges and to further develop the framework, **software architecture knowledge will be very useful**.
- In addition, due to increased involvement of different organizations for creating a single product, the **strategies for protecting the intellectual property of the data shared between different models is also very important in making a digital framework more usable and scalable**. Neutral format options such as the FMI standard can be used to share data without sharing the models (or intellectual property). The software can be created so it can accept the FMI standard files and enable fast data transfer between models. This will result in multiple interactions between these models in a small amount of time, which can then be optimized to get the best possible interaction.
- One of the **keys to successfully implementing this framework is to start by identifying the most critical variables**; these have the largest impact to the outputs of each model and only pass between the models. By doing this, the basic framework can be stood up and the infrastructure of passing information between the models developed on a simpler use case. Once the infrastructure is developed it becomes much easier to add more variables between the models. For example, in the demonstration in this project, the life-cycle modeling team wanted to change the Weibull distribution output from a two-factor Weibull (strength and slope) to a three-factor Weibull (strength, slope, and location). The addition of the location variable would change the strength and slope variable and would require the tweaking of the life-cycle cost model to incorporate the new variable. Since the infrastructure was already set up, it only

required the changing of a few cells in the life-cycle cost model Excel sheet and passing one more variable from the life-cycle model to the life-cycle cost model.

- **Significant delays were experienced at the start of the program due to contractual issues** on all sides. However, the end date was not changed, which resulted in a much accelerated program. As a result, some compromises had to be made that may have reduced the scope of the delivered result

XI. DEFINITIONS

What follows are a set of definitions, terms, and acronyms used in this document. These definitions were gathered from various sources including the internet, reference papers, standards organizations, and the authors of this document.

- **Gear tolerance (AGMA number):** AGMA quality number defines the standard industry quality. Each AGMA quality number is associated with a certain range of 1) number of teeth and pitch diameter, 2) diametral pitch, 3) tooth-to-tooth composite tolerance, and 4) total composite tolerance.
- **Lifing:** The physical method, rules and tools used to calculate the remaining useful life of various parts.
- **Maximum allowable gear face width [Unit: mm]:** Face width is the “thickness” of the gear, defined by the distance between the gear’s two circular faces. If the desired gear has face width larger than a process’ maximum allowable gear face width, then the desired gear cannot be handled by this process.
- **Maximum allowable gear module:** Gear module is a dimensionless number defined by “the number of mm of pitch circle diameter per tooth.” If the desired gear has module larger than a process’ maximum allowable gear module, then the desired gear cannot be handled by this process.
- **Maximum allowable gear outside diameter [Unit: mm]:** This defines the maximum gear outside diameter (i.e., the maximum diameter of the gear on its tip/addendum circle) that a certain process is capable of handling. If the desired gear has outside diameter larger than a process’ maximum allowable gear outside diameter, then the desired gear cannot be handled by this process.
- **Maximum allowable raw material hardness [Unit: HRC]:** This defines the maximum material hardness a process is capable of handling. If the raw material’s hardness exceeds a process’ maximum allowable raw material hardness, then the material cannot be handled by this process.
- **Number of samples:** This attribute represents the number of samples that has been investigated and has generated all other attribute values for the specific manufacturing sequence. This attribute is used when new data comes in to update an existing set of attribute values for the manufacturing sequence. When new set of data, associated with the manufacturing sequence, is input to update the existing manufacturing sequence knowledge, the following two equations are used to update the attribute values:

$$Attribute_{updated} = \frac{Attribute_{old} * N_{old} + Attribute_{new} * N_{new}}{N_{old} + N_{new}}$$

$$N_{updated} = N_{old} + N_{new}$$

where $Attribute_{old}$, $Attribute_{new}$, $Attribute_{updated}$ denotes the attribute value of the existing data, that of the input new data, and the updated attribute value. N_{old} , N_{new} , and $N_{updated}$ are the number of samples represented in the existing data, that of the new data, and the number of samples represented after the update.

- **Pervasive System:** The systems that facilitate the human users by providing the computing power, information, and other services specifically tailored to their needs.
- **Process cost [Unit: \$/part]:** Process cost is defined by the cost for a certain manufacturing process sequence to make the product. In this project, the manufacturing cost is defined to be associated with only the surface roughness as the following equation:

$$Cost = C_{base} * (Surface\ Roughness)^a$$

where Cost is the manufacturing sequence cost for the specified surface roughness-residual stress combination, C_{base} is the baseline cost for that manufacturing/repair sequence and was found in literatures, Surface Roughness is the surface roughness of the product, and a is an empirical parameter. This equation sets up a connection between the gear quality attribute and the manufacturing sequence cost, which provides the candidates to the Optimization Model for their cost analyses.

- **Product rate [Unit: part/hour]:** Product rate describes how fast the manufacturing sequence will handle the material; here the product rate is defined by the number of products made by the manufacturing sequence in one hour.
- **Raw material type:** This defines the type of material used to manufacture the gear. For example, steel.
- **Raw material shape:** This defines the shape of the material. For example, cylindrical.
- **Residual stress [Unit: MPa]:** Residual stresses are stresses that remain in the product material after the conducting the specified manufacturing process sequence. The residual stress is usually not uniform, and the value varies with respect to the depth from the gear material surface to the measured location. Tensile residual stress is defined as positive, and compressive residual stress is defined as negative. In the Manufacturing Model, for each manufacturing sequence, the maximum compressive residual stress is stored. Also, a set of seven residual stress values at seven predefined locations (defined as the depth from the surface) is stored for each manufacturing process sequence to represent their corresponding residual stress profiles.
- **Surface roughness (Ra) [Unit: μm]:** The term surface roughness defines the smoothness of the machined surface after the manufacturing process sequence. Ra is one parameter that could describe the surface roughness, and it is the arithmetic average of the absolute values of the profile height deviations from the mean line, recorded within the evaluation length.
- **Type of gear:** This defines the type of gear. For example, spur gear, helical gear, worm, etc.
- **Type of sequence:** There are three types of sequence associated with the current model – gear manufacturing, gear repair, and bearing ring manufacturing.
- **Weibull Distribution:** A flexible measurement that details the probable distribution associated with the lifetime characteristics of a particular part or service component. Particularly focused on failure-

rate, Weibull distribution is used throughout reliability engineering to anticipate and account for issues of wear-out during development.

XII. APPENDICES

12.1 Appendix A. Definitions of Attribute Names Listed in the Manufacturing Knowledge SQL Database

- **id:** A unique number for each manufacturing/repair sequence
- **DisplaySequence:** An alternative ID that is unique to every sequence in the database. In Georgia Tech's standalone demo website, the sequences applicable to the user requirements are displayed based on this alternative ID.
- **SequenceType:** Indicates the type of process: "1" stands for gear manufacturing process; "2" stands for gear repair process; "3" stands for bearing ring manufacturing process sequence.
- **SequenceName:** This attribute contains the names of the unit manufacturing processes in the sequence
- **Material:** Name of material for which the process sequence is applicable
- **MaterialTypeid:** This ID corresponds to the "Material" attribute. "1" stands for AISI 4320 steel, "3" stands for AISI 9310 steel, "6" stands for AISI 4140 steel
- **Feed:** Feed rate for the gear hobbing process (used as an example of a process condition parameter for the process), if this process is in the selected process sequence. This attribute is not applicable to other sequences.
- **FinishingType:** This attribute contains the name of the finishing process involved in the gear repair process sequence. This attribute is not applicable to other process sequences.
- **MaxHardness:** Maximum material hardness that the process sequence can handle.
- **OutsideDiameter:** Maximum outside diameter of the gear the process sequence can produce.
- **MaxModule:** Maximum module of the gear the process sequence can produce.
- **MaxFaceWidth:** Maximum face width of the gear the process sequence can produce.
- **Sa:** Minimum 3-D arithmetic average surface roughness parameter value produced by the process sequence. This is the mean value derived from a number of parts produced/repared using the relevant process sequence.
- **SaStd:** Standard deviation of the Sa (surface roughness) parameter produced by the process sequence. This value is derived from a number of parts produced/repared using the relevant process sequence.
- **ResidualStress:** Maximum compressive residual stress produced by the process sequence. This is the mean value derived from a number of parts produced/repared using the relevant process sequence.

- **ResidualStressStd:** Standard deviation of the maximum compressive residual stress produced by the process sequence.
- **ResidualStressLocation:** The seven prescribed locations (depth below part surface) at which the residual stress produced by the sequence is measured.
- **ResidualStressAccurate:** A string variable containing the seven residual stresses measured at the seven prescribed locations. Each value is separated by a comma.
- **ResidualStressAccurate1:** Variable containing the residual stress value measured at the first prescribed location. It is the same value as the first value stored in "ResidualStressAccurate".
- **ResidualStressAccurate2:** Variable containing the residual stress value measured at the second prescribed location. It is the same value as the second value stored in "ResidualStressAccurate".
- **ResidualStressAccurate3:** Variable containing the residual stress value measured at the third prescribed location. It is the same value as the third value stored in "ResidualStressAccurate".
- **ResidualStressAccurate4:** Variable containing the residual stress value measured at the fourth prescribed location. It is the same value as the fourth value stored in "ResidualStressAccurate".
- **ResidualStressAccurate5:** Variable containing the residual stress value measured at the fifth prescribed location. It is the same value as the fifth value stored in "ResidualStressAccurate".
- **ResidualStressAccurate6:** Variable containing the residual stress value measured at the sixth prescribed location. It is the same value as the sixth value stored in "ResidualStressAccurate".
- **ResidualStressAccurate7:** Variable containing the residual stress value measured at the seventh prescribed location. It is the same value as the seventh value stored in "ResidualStressAccurate".
- **Tolerance:** Dimensional tolerance of the critical part feature produced by the process sequence. For gear manufacturing/repair sequences, this is defined as the AGMA tolerance number.
- **ProductRate:** Production rate for the process sequence.
- **ProcessCost:** Unit process cost for the process sequence.
- **NumberOfSample:** Number of parts inspected to derive the mean values stored in "Sa" and "ResidualStress".
- **MicroPittingMaxDepth:** Maximum depth of micro-pitting for which the repair sequence is viable. Assumed to be 40 mm for the repair sequences considered in the project.
- **Pri:** This is an alternative ID (but it is not unique for each process sequence). A sequence with "Pri" = 1 is either the baseline case or the alternative case corresponding to Sentient Science's sensitivity study.

Note: String variable containing the necessary description of the process.