Final Project Report

Cognitive On-demand Design Advisor	
Principal Investigator / Email Address	N/A
Project Team Lead	International TechneGroup Incorporated (ITI)
Project Designation	21-01-05
MxD Contract Number	2022-01
Project Participants	Raytheon Technologies Microsoft
MxD Funding Value	N/A
Project Team Cost Share	N/A
Award Date	August 15, 2022
Completion Date	November 15, 2023

DISTRIBUTION STATEMENT A. Approved for public release: distribution unlimited.
This project was completed under the Technology Investment Agreement W15QKN-19-3-0003, between Army Contracting Command – New Jersey and MxD. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the Department of the Army.

mxdusa.org
@mxdinnovates
info@uilabs.org

1415 N. Cherry Avenue
Chicago, IL 60642
(312) 281-6900

This page intentionally left blank

mxdusa.org
@mxdinnovates
info@uilabs.org
1415 N. Cherry Avenue
Chicago, IL 60642
(312) 281-6900

TABLE OF CONTENTS

I. EXECUTIVE SUMMARY

Current design platforms fail to provide real-time feedback from downstream efforts in time to mitigate the cost and schedule impact of design flaws. Facilitating this feedback is elusive without formal representation of multiple manufacturing, supplier and life-cycle attributes. The Raytheon and ITI team proposed this project to implement an Artificial Intelligence (AI)/Machine Learning (ML) based design advisor to provide design engineers viable options to mitigate design and cost risk, decrease Engineering Change Orders (ECOs), and extend product life by addressing obsolescence in electronics. The team's Cognitive On-Demand Design Advisor (CODA) is accessible to diverse users and generates data-driven, system agnostic, and forward-looking design recommendations within the user's design environment. CODA is demonstrated via a Circuit Card Assembly (CCA) use-case however the framework approach allows for additional advisement models to be incorporated.

During the project, the team identified that current approaches leverage manual efforts leveraging market relationships, supplier information, and SME knowledge to identify obsolescence risk in components. This process takes .25 hours per component and requires design reviews to manually manage the data. By automating this process utilizing AI based model approaches, components can be analyzed and tagged within the design without manual intervention. This allows for savings of up to $932K/year in addition to improvements in flagging obsolescence risk early to reduce downstream engineering change.

The CODA team engaged the Microsoft Azure Machine Learning Workspace with the support of Microsoft engineers to pull together key supplier and internal historical data to calculate obsolescence using a Random Forest and k-nearest neighbors (KNN) approach. This model was integrated into the ITI Linked Intelligent Master Model (LIMM) application which provides the necessary interoperability between the engineering workspace and the machine learning model endpoint. The LIMM environment provides additional analysis which provides key feedback to the design engineer to see trade-offs between component obsolescence risk along with cost and performance.

Machine Learning models are only as good as the data which is used to train the models. As a result of this project, the team was able to leverage a large database of information to train the model as well as identify future information that would improve the model results. This information requires collaboration with the supply chain as well as the industry at large. There is an opportunity to grow an industry wide dataset which is managed by the defense industries technical community and leveraged by multiple partners. This dataset can be the foundation for small and medium-sized businesses to conduct their own analysis and integrated into larger OEMs for advanced AI analytics.

II. PROJECT DELIVERABLES

The following list includes all deliverables created through this project.

Table 1: CODA Project Deliverables

#	DELIVERABLE NAME	DESCRIPTION	FORMAT OF DELIVERY
1	Bi-weekly Technical Reports Membership Review Presentation	The project team met bi-weekly throughout the project including one membership review presentation half-way through the project.	PPT
2	Final technical report – white paper	This document	DOC | PDF
3	Demonstration – Outcome and Report	Video of demonstration using publicly available design | information with companion presentation report	Video | PDF
4	System Architecture and Integration Framework	System Requirement Specification (SRS)	PDF
5	Network Architecture	Software Development Specification (SDS)	PDF
6	AI Design Advisor Tool	Software Installation and Setup Guides – requires Siemens Expedition and LIMM	PDF | MSI | EXE | DLLs
7	Test and Validation Report	Test and validation approach and results based on historical data	PDF
8	Implementation at Design to Manufacturing Site	Approach for implementation and production concerns	PDF
9	Detailed Case Study	Case study providing implementation and results – best practices and lessons learned	PDF
10	Technical Demonstrations	Video of demonstration for technical reviews and sharing of technology within the project	Video
11	Developer Documentation	Documentation detailing the development process and design of the solution	PDF
12	User Manuals	Documentation on using the solution	PDF
13	Transition Plan	Document detailing transition plan	PDF

III. PROJECT REVIEW

Use Cases & Problem Statement

Advancements in AI can provide intelligence to design engineers that takes years of knowledge and direct access to data from suppliers and manufacturing. No system or framework exists that provides a streamlined capability to connect the tools required to make informed decisions during design. CODA provides the tool integration, platform, and process framework to create an intelligent ecosystem connecting design engineers to models which can provide assistance in design.

As a **design engineer**, I want to ensure selected parts are available for the planned production and product lifetime to continuously **reduce Life Cycle Cost and eliminate performance impact from engineering change orders and mid-life obsolescence part changes**.

Furthermore, the engineering community has no infrastructure to share across industry the predicted obsolescence or the modeling of ECOs related to obsolescence. CODA provides the steppingstones to create the first industry wide machine learning model-based approach to providing obsolescence prediction across the defense manufacturing base within the next 2-5 years.

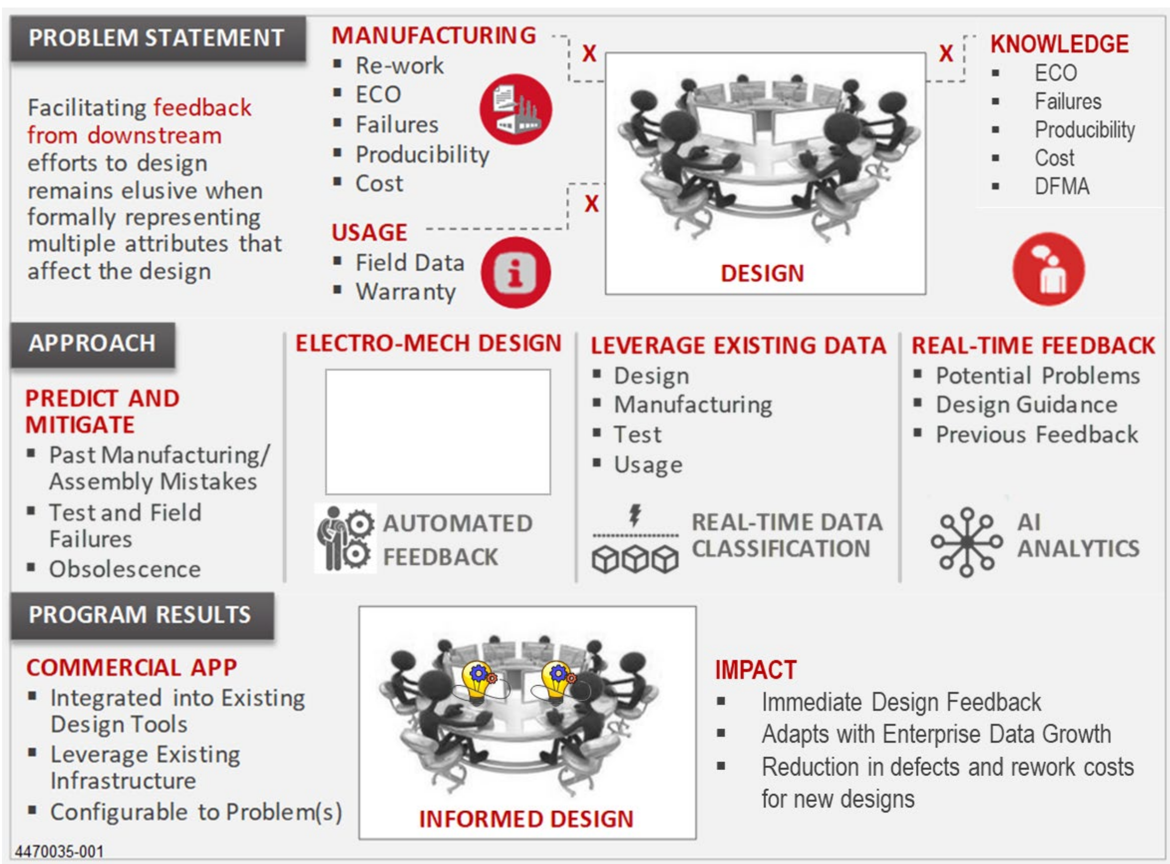


Figure 1: CODA Executive Summary Chart

Scope & Objectives

The project focuses on obsolescence of electronic components purchased within the supply base within the publicly available domain set of data as well as internally available data within the Raytheon environment. The public demonstrations will be based on the publicly available data however data types will be identified that go beyond the scope of the project's implementation.

The objective of the project is to allow the design engineer to work within their design space (Siemens Xpedition – Layout) and obtain immediate obsolescence data based on the components within their design. The prediction will leverage an Azure hosted machine learning model which identifies the predicted obsolescence score as well as the suggested components to use based on the component's requirements.

Planned Benefits

There are several planned and realized benefits for CODA.

1. Provide design engineers direct feedback within the design color coded which can quickly view obsolescence scores and issues in the source where the issue can be assessed and addressed quickly
2. Allows the obsolescence team to focus on higher risk components earlier to address concerns with the supplier
3. [Future] Identifies gaps in the current data to capture to improve results and analysis
4. [Future] Provides the framework and infrastructure for industry wide analysis which can utilize more information to provide better obsolescence management within the defense community

Specific user problem	The user's design engineer role creates a new or revised circuit card design for a company that designs products with life expectancies of greater than seven years and the product continues to be serviced throughout its life. The problem is that hundreds of parts are used on a circuit card and many have limited life due to technology improvement. At some point, these components will not be available for manufacturing or service. Others impacted by the problem include: manufacturing engineering, purchasing, logistics and support
Existing state	Designers select components from libraries. The libraries may contain obsolete components unbeknownst to the designer. The manufacturing engineering team and purchasing team evaluate each component to make sure that the component is available, but no studies are performed to aid in predicting the problem and to correct a problem requiring engineering changes and potentially redesign.
Future state	The design engineer selects components and periodically requests an obsolescence analysis from CODA. The feedback tells the engineer whether components are available or not and also helps generate an obsolescence report that can be used to align changes based on events to minimize the number of future changes.

mxdusa.org
@mxdinnovates
info@uilabs.org

1415 N. Cherry Avenue
Chicago, IL 60642
(312) 281-6900

Specific user solution	• The approach will be to integrate with the design tool and extract component and user feedback to transform the information into intelligent search criteria. The information would be evaluated continuously during design. • The cloud addresses the complex and large volume of data used to make inferences regarding historic manufacturing/supplier issues for the use-case of obsolescence. • The team will address the solution scalability across multiple designers, designs, tools, and data, including other design feedback (rules or physics-based). Leveraging ITI's integration service provides the ability to segregate the data requirements from design and manufacturing environments and the cloud based actionable data.

IV. TECHNICAL APPROACH

To realize the CODA project, the team utilized existing tools and infrastructure from the Manufacturing Process Driven Design (MPDD) program such that the team could focus directly on the AI and integration components for the design engineer. This approach allowed the team to utilize a proven framework that connects engineering, cost, producibility, and manufacturing models and expand the platform's capabilities for AI driven model development. The technical approach is broken down into 3 key parts: machine learning model development and training, engineering workspace, and the enterprise integration platform (LIMM).

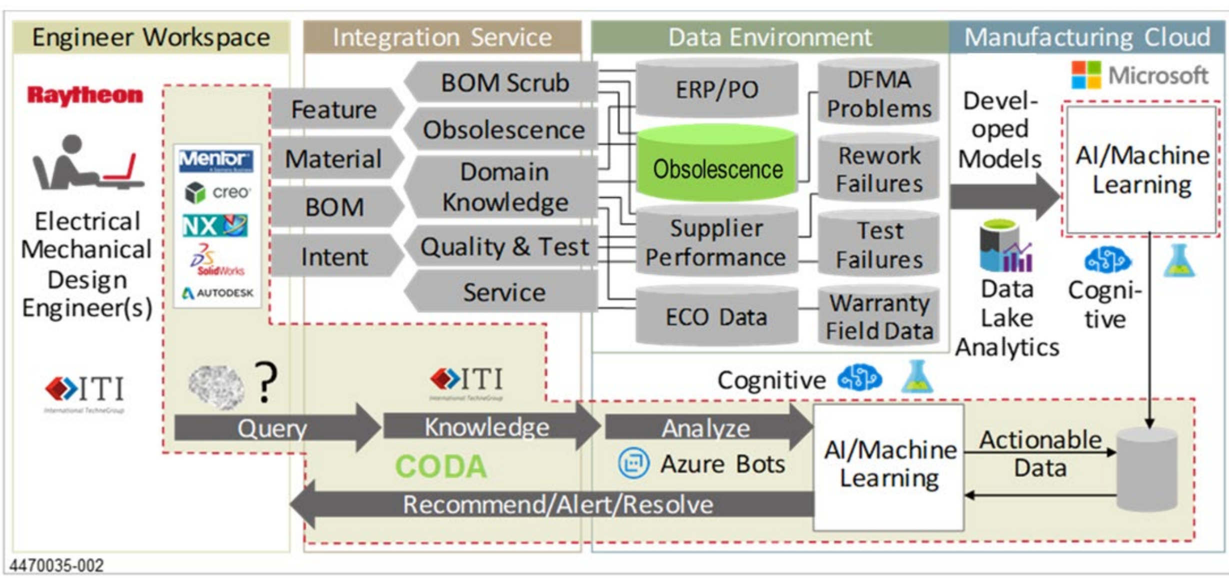


Figure 2: CODA Framework / Vision

1. Machine Learning Model Development and Training

Data Engineering

Once the CODA program kicked off the team collaborated with CCA Engineers to develop a non-functional model with commercially available electrical components that the CODA team would be able to use for a demo of the program. The CODA team started to investigate one of the internal Raytheon databases that was proposed for this project (iPASS). The team was tasked with aggregating data that was applicable to Obsolescence and parametric values associated with the electrical components identified in the Bill of Material (BOM) for the model circuit card developed for the program. For the scope of this project the team needed to ensure that the data aggregated was commercially available.

The CODA development team worked closely to determine how to extract the entire database and retain the data that was needed to successfully complete this program. After discussions with the database managers, the CODA team was provided access to an endpoint which an Application Program Interface (API) could be developed to aggregate the data. The data was aggregated from the iPASS database for all components in the database. The CODA team identified the data entries that were applicable to the Obsolescence of the component as well as relevant parametric data that was also commercially available. The Raytheon CODA team reviewed the dataset that was identified with the subject matter experts and was provided approval to utilize this data in the ITI Azure environment.

Now that the data has been extracted, applicable data was identified and approved for external use, the CODA team started to analyze the dataset with regards to quality of data from a machine learning perspective. After analysis into the database, the team realized that critical data was missing. Figure 3 shows the histogram of the available data that was identified as applicable and commercially available by the CODA team. Some of the complete data entries that are identified (i.e. has_bom_part) are Boolean datapoints that will have minimal effect on the training of the machine learning model. Other data entries are only applicable to specific categories of components (i.e. shape, mounting features). Critical data to train the machine learning model includes the color coding of the manufacturing part number obsolescence (mpn_obs_color_code).

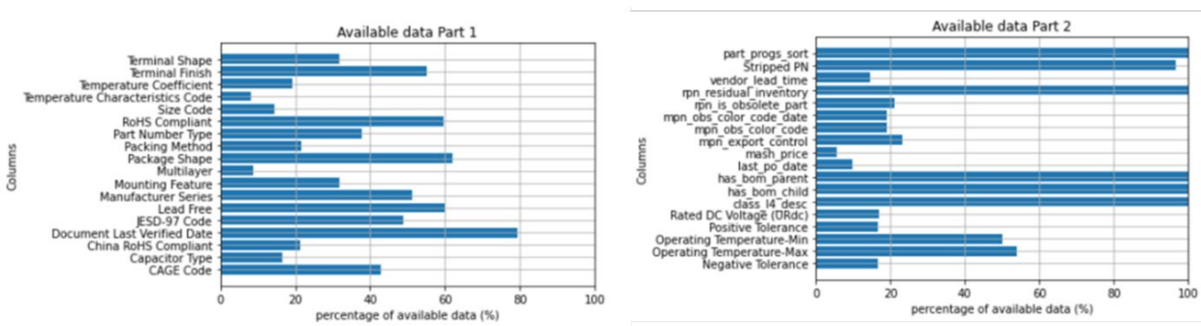


Figure 3: Histogram of Available Properties

Provided with this challenge, the CODA team needed to come up with a solution to integrate the iPASS data while also collecting the necessary data to train the machine learning models. After brainstorming potential solutions, the team decided to develop an API query the supplier Digikey, which is a commercial provider for electrical CCA components. The team decided that this was the most reasonable path forward due to the accessibility of the data along with the scope of the program to provide commercially available data. The API was developed and merged with the iPASS data to provide a sufficient dataset to develop the machine learning models.

With just over 20% of the manufacturing part number obsolescence color code available in the internal Raytheon iPASS database, the team turned to using the Digikey obsolescence labels to train the model. By switching to the Digikey obsolescence labels, the team gained insight of what the whole industry considers obsolete but loses the knowledge to why that part is obsolete. Digikey states that most manufacturers omit the reason why a component label has changed due to business strategy.

The Digikey obsolescence labels were needed to train the model to show proof of concept of the technology, but the Raytheon based labels can be inserted back into future work when they're available.

When the team pulled the data into the Azure environment, they noticed that all of the data entries were represented as strings. Since the Python based machine learning models only accept numerical data, some natural language processing techniques needed to be applied.

For the parametric values (i.e.: voltage resistance, etc.) the unit character was removed from the string and the numerical value was casted into an integer or float. This means for a voltage entry such as "5V" becomes an integer '5'. If there was a missing entry during training, -1 was entered into the field.

For categorical columns (i.e: supplier, component type, etc.) an Ordinal encoder was applied to convert the values into integers (0 to N categories – 1). If a category entry was missing during model training, -1 was filled in. And when the trained model received a new category that wasn't in the training set, -2 was entered.

The final step was applying a feature scaling method to the data so that each feature with different units and ranges is converted into a uniform unitless feature. This allowed the model to not make a single feature overpower the dependence on the obsolescence prediction. The team decided to use the Standard Scaler (a.k.a z-score) to remove the mean and scale based off of the data's variance.

The journey of this program does not stray from the inherited struggles of data engineering when developing machine learning models. The goal of machine learning is to provide the most accurate models as possible, in order to do so, engineers must first, ensure that they have quality data. The Pareto rule can be applied to summarize this program where 80% of the work is done on data engineering where the following 20% is focused on model development and deployment.

Model Development

After the CODA team determined with the two database queries (internal Raytheon iPASS as well as Digikey) that they were receiving quality data, the machine learning models could start to be developed. The CODA team investigated multiple machine learning approaches but eventually decided on two supervised learning models. The team decided to utilize the Random Forests library as the characterization tool. The Random Forests machine learning model is used to mimic the design engineers' decision making when selecting components to provide the most accurate model that will predict obsolescence. A probability score is provided to the user for each component which displays the probability that a component is obsolete.

Random Forest Image

If a component has a probability of being or becoming obsolete, the developed tool will provide a recommended component to use for replacement. The recommended component is generated through the content-based filtering approach. The content-based filtering function uses a cosine similarity mathematical algorithm to calculate the distances of the dataset to the obsolete component as the input to the model. The cosine similarity metric was chosen so that each parametric value for a given component has an equal importance in recommending the closest active component. The smaller the distance value, the more similar the replacement component is to the obsolete component.

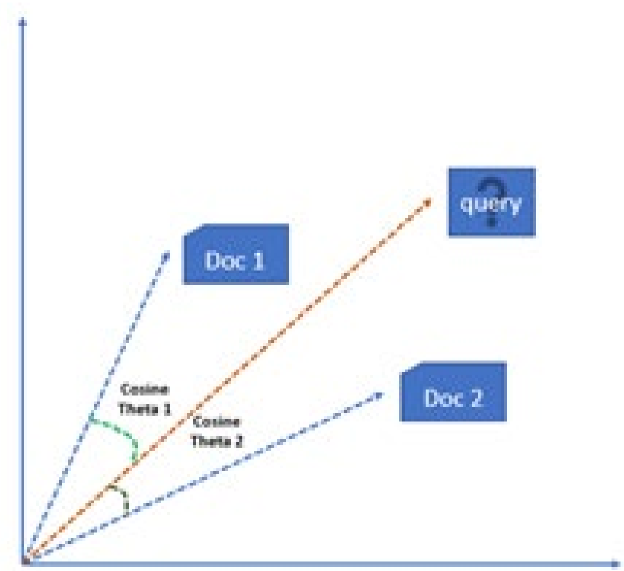


Figure 4: Random Forest Image

Link: https://aurigait.com/blog/recommendation-system-using-knn/

Model Training and Deployment

The team's machine learning pipeline was developed using the Azure Machine Learning (Azure ML) service in the cloud to leverage their on-demand resources to quickly scale their solution. The figure below shows the machine learning training pipeline in the Azure ML.

Each block is a containerized Python function where the OS and computing power can be defined for each container. This allowed the team to add and remove any part, concisely display the workflow and designate the proper computing power to each step to reduce costs.

Within the pipeline, the team used the MLFlow machine learning lifecycle tool to evaluate the model's performance and save the model with its version control features. The figure below shows the confusion matrix of the trained model along with the accuracy in the caption.

A decrease in the model accuracy can be setup as an alert to retrain the model. Especially in costly errors such as incorrectly predicting an obsolete component as active (large number in the bottom left corner of the confusion matrix.

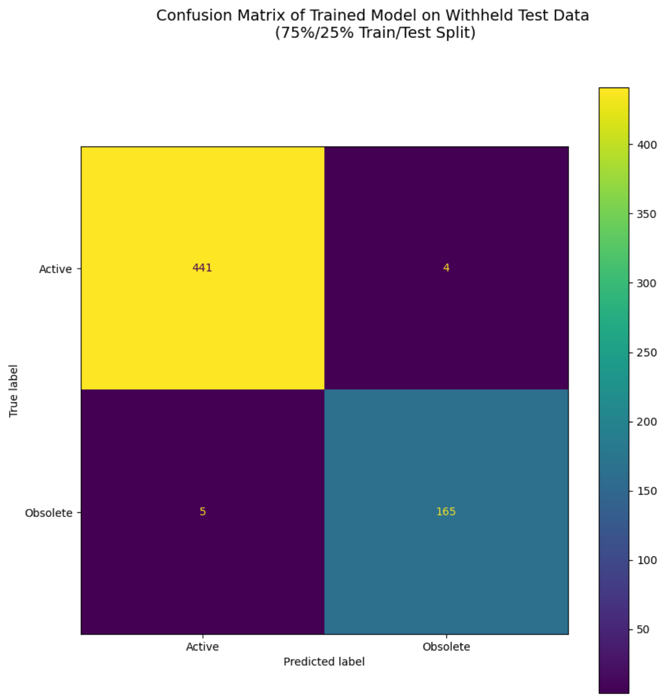


Figure 5: confusion matrix results, model had an accuracy of 98.5%

Once the model was trained, it was deployed to an Azure online endpoint. Azure model deployment platform generates the URL and authentication keys, operational metrics (i.e.: request per minute) and example code to consume model predictions in multiple programming languages. See the screenshot below to see the deployed model in Azure.

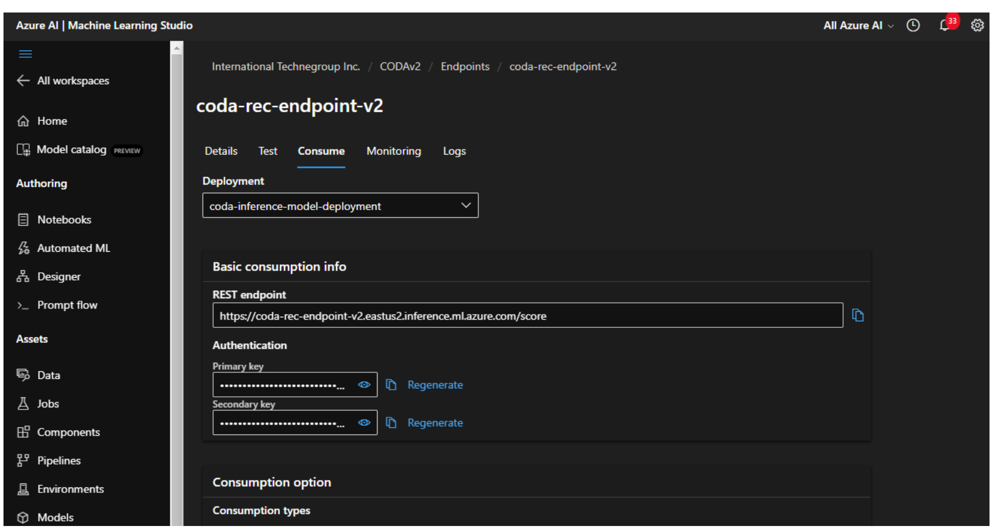


Figure 6: Deployed recommendation model's REST endpoint

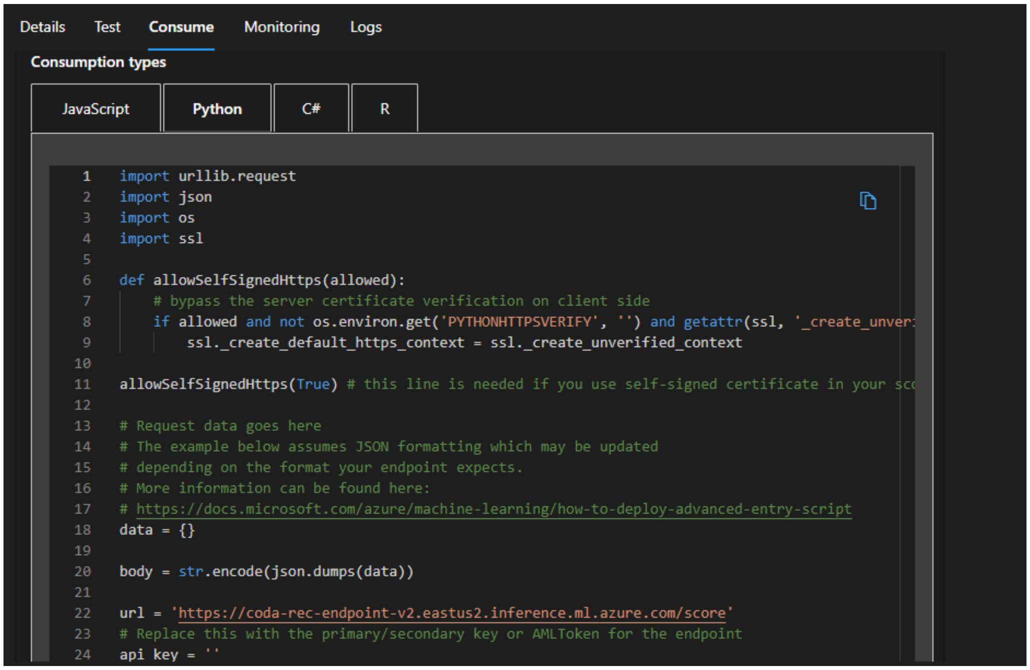


Figure 7: Example Python code to make API calls to the recommendation model

The example code was used to generate an API connection between Azure and Siemens Xpedition to show the model's recommendations as the design engineers are selecting components.

2. Engineering Workspace

The Engineering Workspace consists of the tools that engineers leverage on a daily basis for their design environment. The CODA team wanted to leverage this space as the interface for obtaining the CODA analysis results to minimize the additional work or manual efforts of consolidating obsolescence scores and feedback. To achieve this, the team had to create new add-ins to the Siemens Xpedition (formerly Mentor Graphics) platform. Most components are chosen during the actual board layout phase so it was decided to perform this integration into the PCB Layout tool though other tools such as the designer can be leveraged if parts are linked to the design.

Siemens Xpedition recommends utilizing their scripting capability via VBScript for automation and customized user actions. An older approach that was documented several years ago was also identified to create a C++ dll that provides direct add-in integration into the application's toolbar and menu design.

The team designed the desired interface and interactions conceptually and began work on coding the integration.

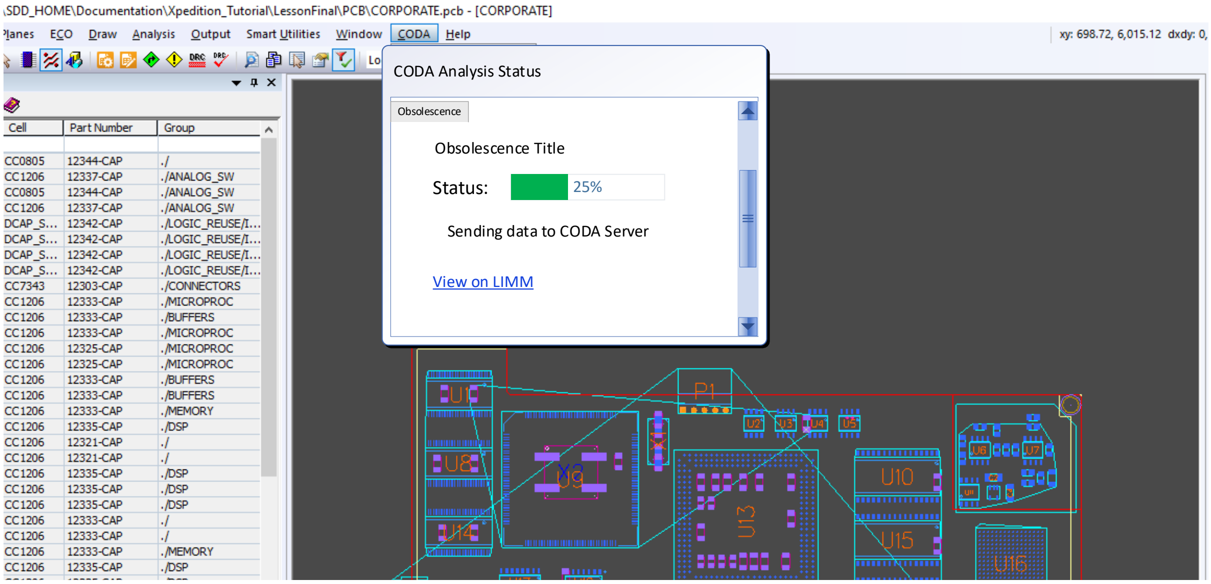


Figure 8: Mockup UI

It was identified after the first integration study that the VBScript method was not integrated in such a way that made the GUI seamlessly integrated with the Xpedition environment. VBScript required the GUI to use pop-up menus and the capabilities for the user interface were lacking rich controls and stability. Xpedition required all programming to be done within the software interface. Figure 9 shows the first revision with the VB based integration.

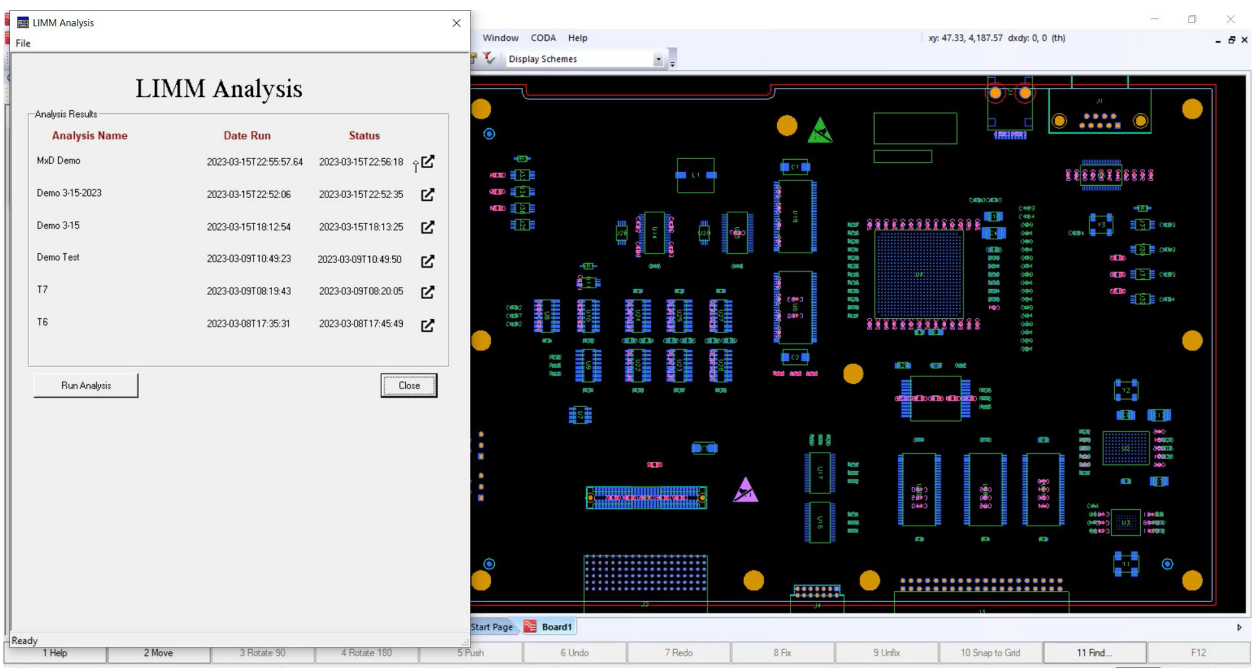


Figure 9: 1st Revision Integration with CODA

The team looked at other alternatives and found documentation from Mentor Graphics prior to the Siemens acquisition that detailed a C++ approach to create a rich add-in control using ATL. Documentation was legacy however the team was able to generate a new add-in using this method. The team documented the interfaces and began the development utilizing existing LIMM automation scripts and the C++ documentation found within the AATK toolkit's packaging (https://sourceforge.net/projects/uwtoolbox/files/Expedition%20Enterprise%20AATK/).

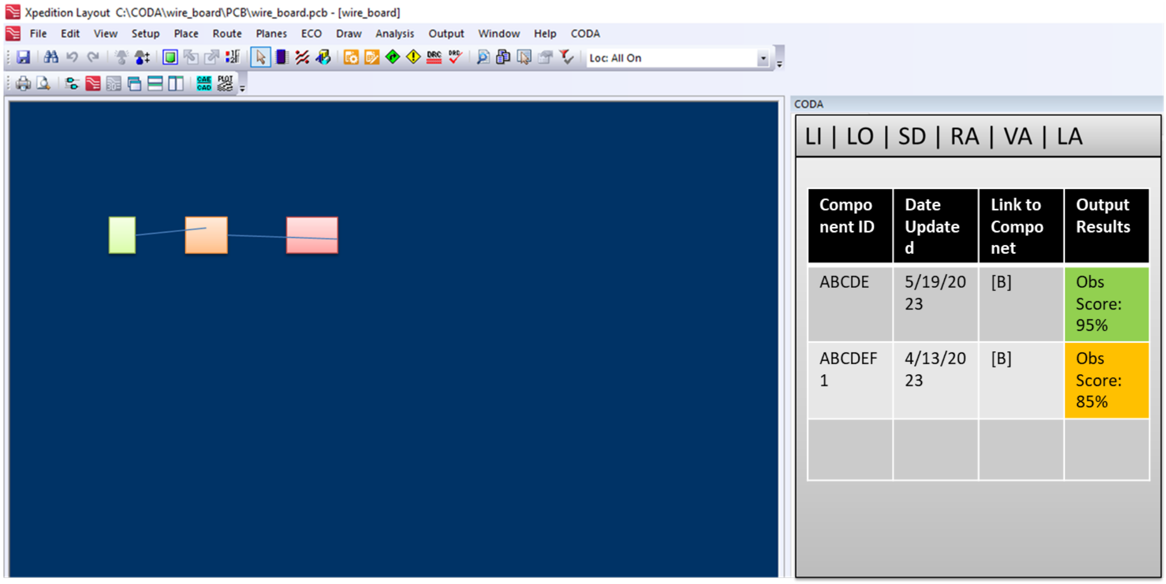


Figure 10: C++ Add-in Mockup

After mocking up the GUI, the add-in was developed and linked to the Xpedition menu using the customization capabilities within Xpedition.

```
Dim pcbApp
Set pcbApp = Application

Dim stdToolBar
Set stdToolBar = Gui.CommandBars("Document Menu Bar")

Dim stdTBCtrls, button
Set stdTBCtrls = stdToolBar.Controls

menupos = stdToolBar.Controls.Count()
Dim menu
Set menu = stdTBCtrls.Add(cmdControlPopup,,,menupos)
menu.Caption = "&CODA"
Set button = menu.Controls.Add(cmdControlButton,,,-1)
button.Target = ScriptEngine
button.Caption = "Run Analysis"
button.ExecuteMethod = "LaunchCoda"

Scripting.DontExit = True

Sub LaunchCoda(nId)
  'MsgBox "LaunchCoda"
  side = 2    ' right      0 = left, 1 = top, 2 = right, 3 = bottom
  Set output = launchAddin("CodaAddin.CodaCtrl.1", "CODA", "", side, "CTRL+ALT+C")

  If Not (output Is Nothing) Then
      ' make visible
      output.Visible = True
      ' get directory
      'dirReq = inputbox("Directory to display?")
      'dirReq = "C:temp"
      'Set theTab = output.Control.AddTab("Dir")
      'Scripting.AttachEvents theTab, "Tab"
      'theTab.RunProgram "%COMSPEC% /c dir " & dirReq, False   ' don't block
  Else
      MsgBox "Can't find the CodaCtrl Addin"
  End If

End Sub
```

Figure 11: Customization of Xpedition Menu and Action to Launch CODA Add-in

The team utilized an embedded object browser within the menu such that LIMM web-based controls and web API could be consumed within the add-in. This provides a richer experience for the end user and an ability to provide future integrations and capabilities for the user for any interface through LIMM.

A sample add-in is provided as part of this project which can be customized for future Xpedition add-ins.

3. Enterprise Integration Platform (LIMM)

The team leveraged ITI's Linked Intelligent Master Model (LIMM) platform to provide the communication and security infrastructure required to interface with the generated ML and recommendation framework. LIMM provides out of the box collaboration and integration to leading design and analysis tools. By leveraging LIMM the team could focus on the data engineering, model development, and visualization to the user versus development of the integration and security required.

The team took advantage of the LIMM API to provide the concept project selection, analysis management, and storage / packaging of results within the Xpedition PCB Layout GUI. The API provides the framework to submit the required design information through LIMM, package the format for the ML endpoint, and retrieve the results. LIMM then stores this information for each analysis such that the users can access current and historical results.

By leveraging LIMM, the Xpedition integration also provides the ability to run additional analysis tools including Ansys, HFSS, producibility, and cost analysis in addition to the CODA analysis.

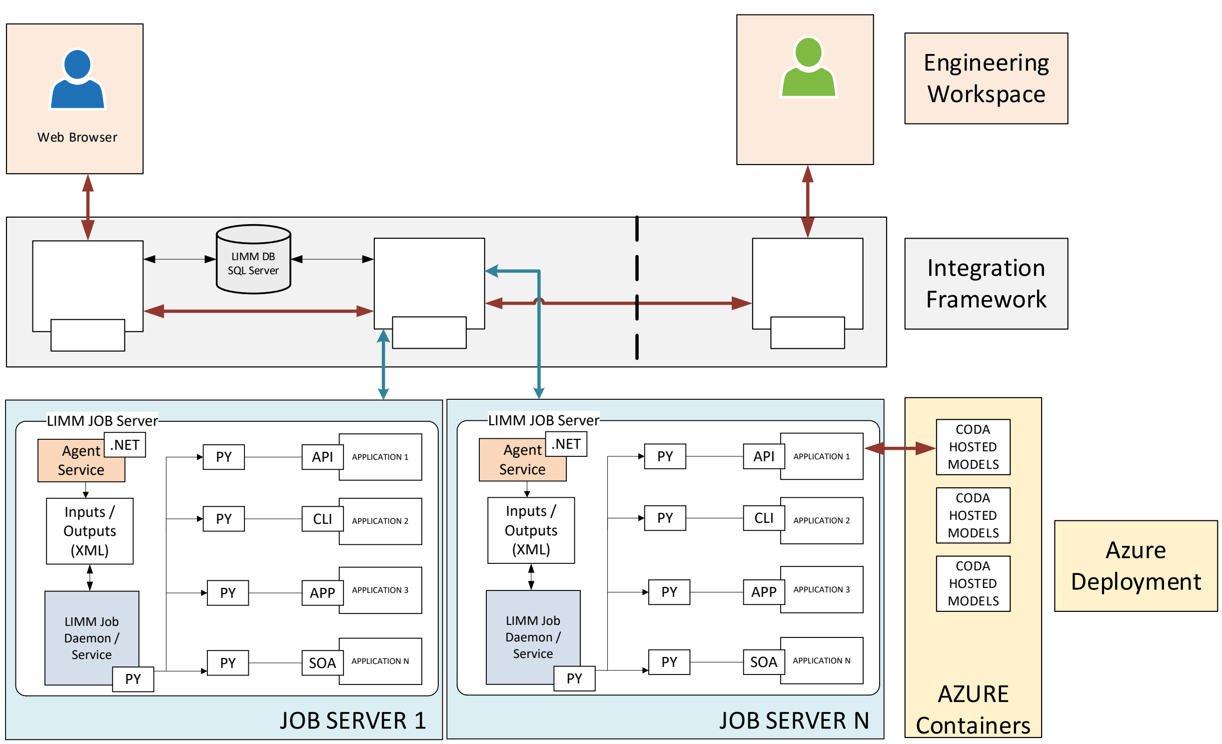


Figure 12: CODA Deployment Diagram

mxdusa.org
@mxdinnovates
info@uilabs.org

1415 N. Cherry Avenue
Chicago, IL 60642
(312) 281-6900

To provide flexibility in the development, execution, and demonstration of the CODA solution the team managed two environments for the project. The internal environment includes the Raytheon infrastructure and servers with connection to Azure tenant government cloud environment. The external or demonstration environment includes a similar infrastructure for Xpedition and LIMM and leverages ITI's Azure tenant for the model development and deployment.

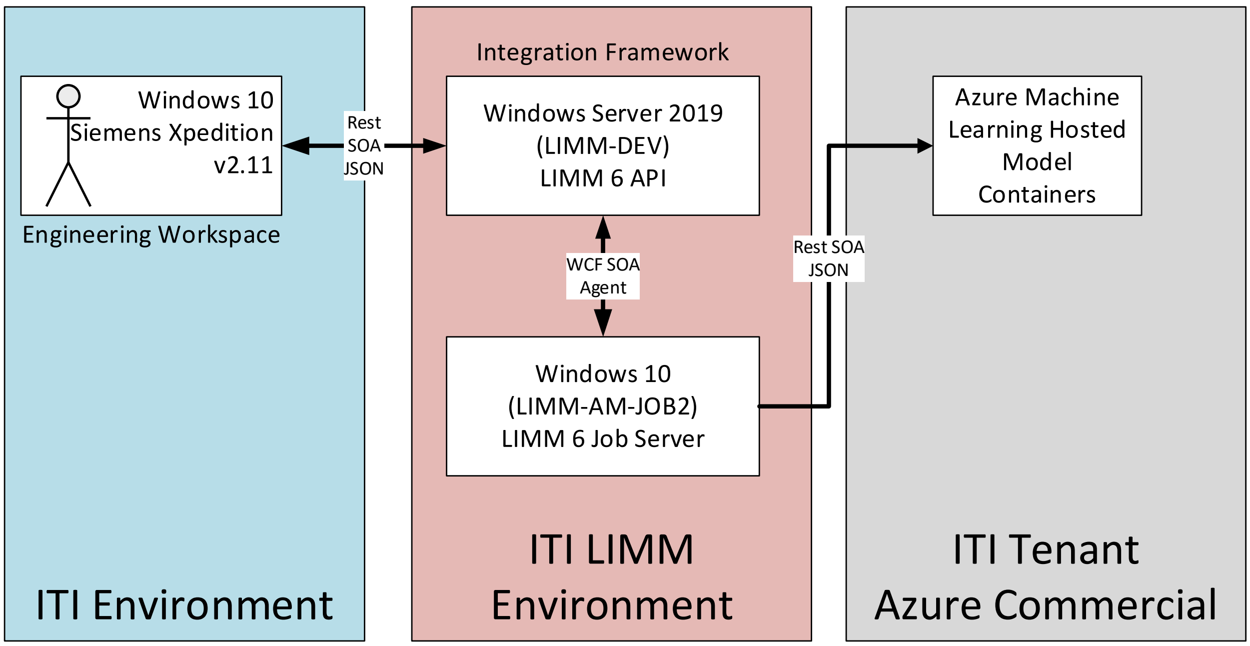


Figure 13: Demonstration Environment

V. RESULTS

Table X: CODA Technology Deliverables

#	DELIVERABLE NAME	DESCRIPTION	FORMAT OF DELIVERY
1	LIMM CODA Adapter Python Example	The adapter used by LIMM to send design information into the ML model and send results back to LIMM	*.py Python File*
2	Azure ML Python Model(s)	Python code(s) used for ML model development	.py Python File
3	Xpedition Add-in Example	Add-in C++ project code example	.zip Visual Studio Project Files
4	Demonstration & Documentation	Videos and documentation of setup, development, and user documentation	.mp4 and .pdf

System Overview

CODA provides the enterprise framework to reduce the efforts in the integration of engineering design and downstream models. The tools leveraged provide the process to perform the data engineering, ML model development, deployment, and integration within the design community.

Each of these is integral to the creation of an AI driven design advisor. Designers work within their environment and subject matter experts work to optimize the AI models through future data capture, analysis, and engineering.

The AI movement will continue to provide rapid improvements in the design and manufacturing processes and CODA will be crucial for the rapid implementation and integration of these models. CODA has the potential of replacing 100s of man hours sifting through design components and manually evaluating risk of obsolescence as well as providing design engineers instant feedback and recommendations without the need to manually generate spreadsheets and review dated obsolescence information.

Additional work is required to improve the obsolescence scores by capturing additional industry information and improving the models which is typical and a necessary component to the AI approach where data training and model development continues to improve.

System Requirements

Obsolescence management is a time-consuming process that takes a team of engineers in the background working daily to examine new and existing designs to identify obsolescent and at-risk components. They use expertise gained in working within this environment for many years, the relationships they have built with the suppliers, and the socio-economic and political issues that transpire. This information is captured on a bi-annual basis when a design is marked for review. The information required is gathered through many different data sources and captured for downstream identification for design engineers. It is up to these designers to review the component information and make decisions based on the data which can be up to 6 or more months old.

The team currently assesses over 16,000 components and in 1 year can assess over 44,000 components. Each part can take 8-15 minutes or longer to assess. In addition, design engineers must review the BOM audit reports after choosing the components within the design and make design changes when issues are identified. Issues can be found within the concept design, detail design, manufacturing, or after release.

System Architecture

The Cognitive On-Demand Design Assistant (CODA) framework provides guidance for downstream engineering and manufacturing change issues early within the design process. While the program focuses on obsolescence of electrical design components, the system architecture requires a robust and flexible approach that can integrate to additional tools, data, and models to provide assistance to other downstream issues and design information. This can include generative design, obsolescence of other design elements, predictive analysis, manufacturing speed, etc.

The overall system approach is shown in figure 14 below.

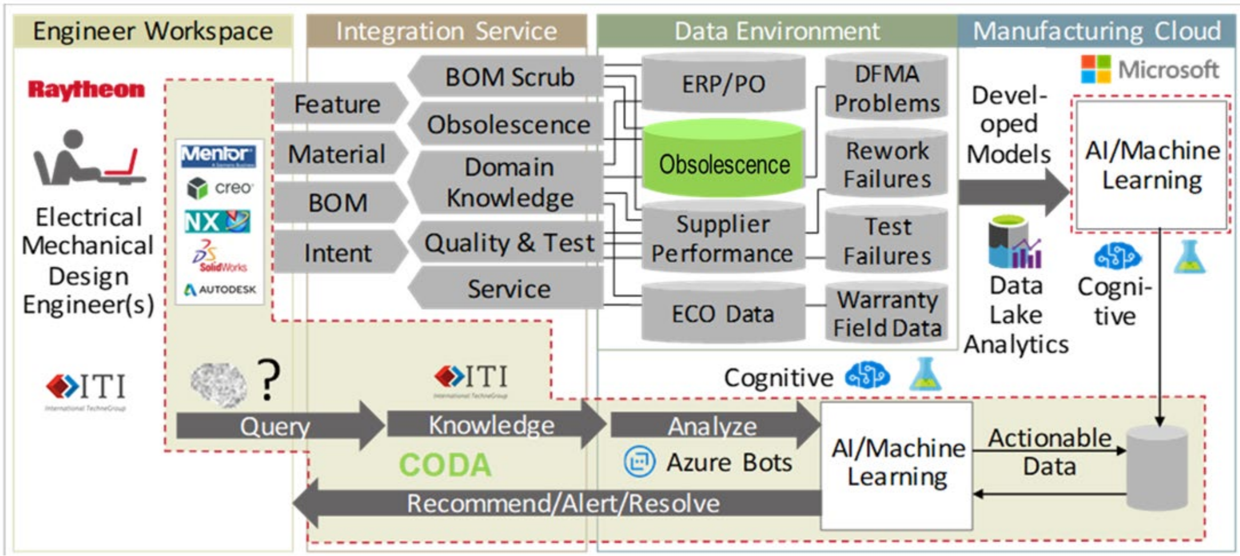


Figure 14: CODA System Approach

The system architecture identifies the 4 building blocks of CODA: engineering workspace, integration service, data lake / environment, and the AI/ML cloud development.

CODA begins with the development of the AI/ML models that are later integrated into the engineering workspace. The system architecture includes leveraging existing data information within the Raytheon data ecosystem, their suppliers, and rules / analysis generated from subject matter experts.

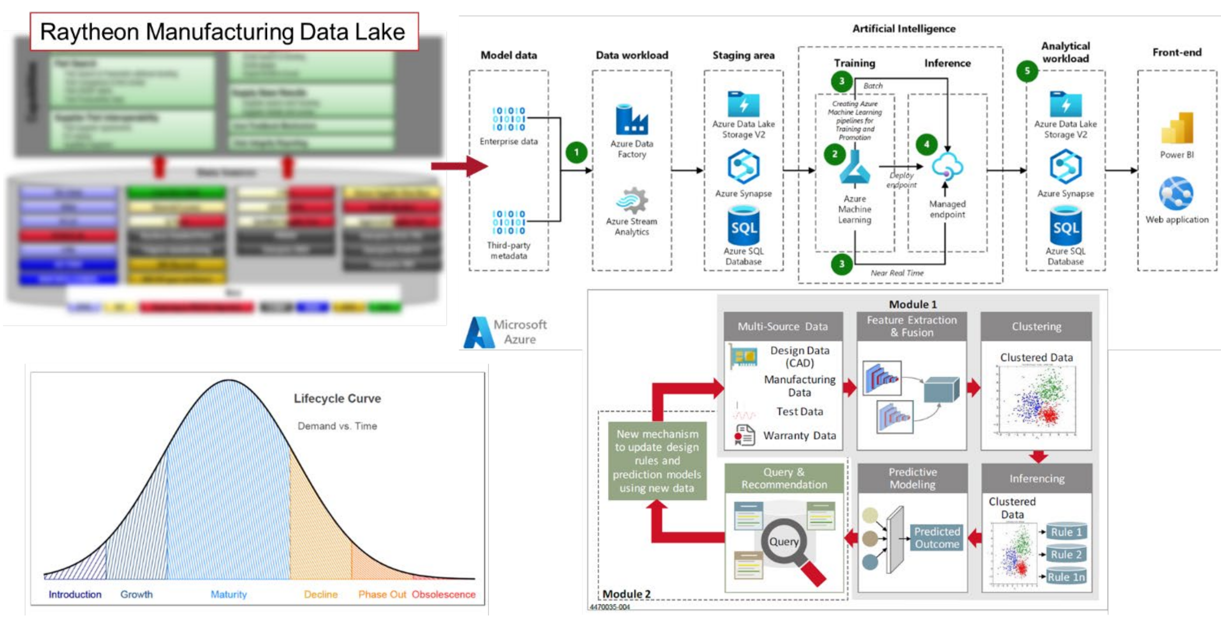


Figure 15: Azure Cloud and Data Engineering Architecture

This is integrated using the integration service layer which the team leveraged ITI's Linked Intelligent Master Model (LIMM). The integration service layer provides the integrations into the models necessary for design engineers to make quick decisions in a collaborative knowledge base driven environment.

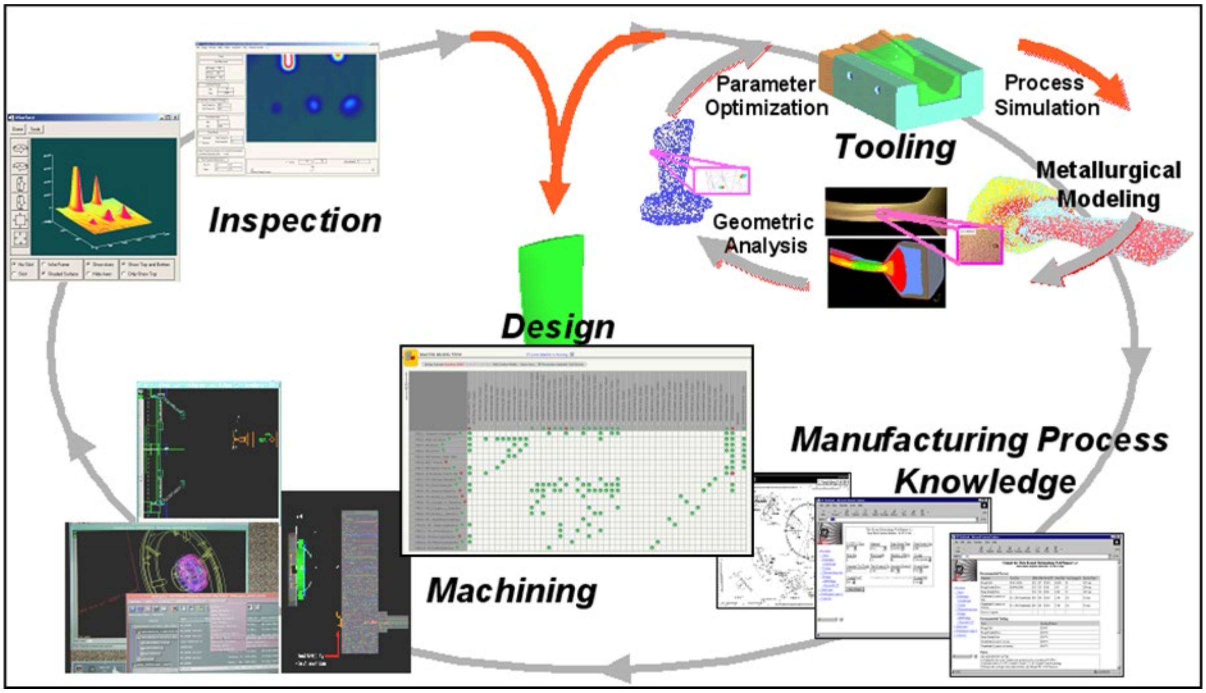


Figure 16: Linked Intellignet Master Model (LIMM) Process Flow

To reduce the manual efforts to tie design components to the obsolescence scores, LIMM provides direct integrations to leading CAD and other systems to bridge model results and other knowledge information. The engineering workspace provides the results to end users in familiar tools and/or tied to the actual design to quickly relate results to the component.

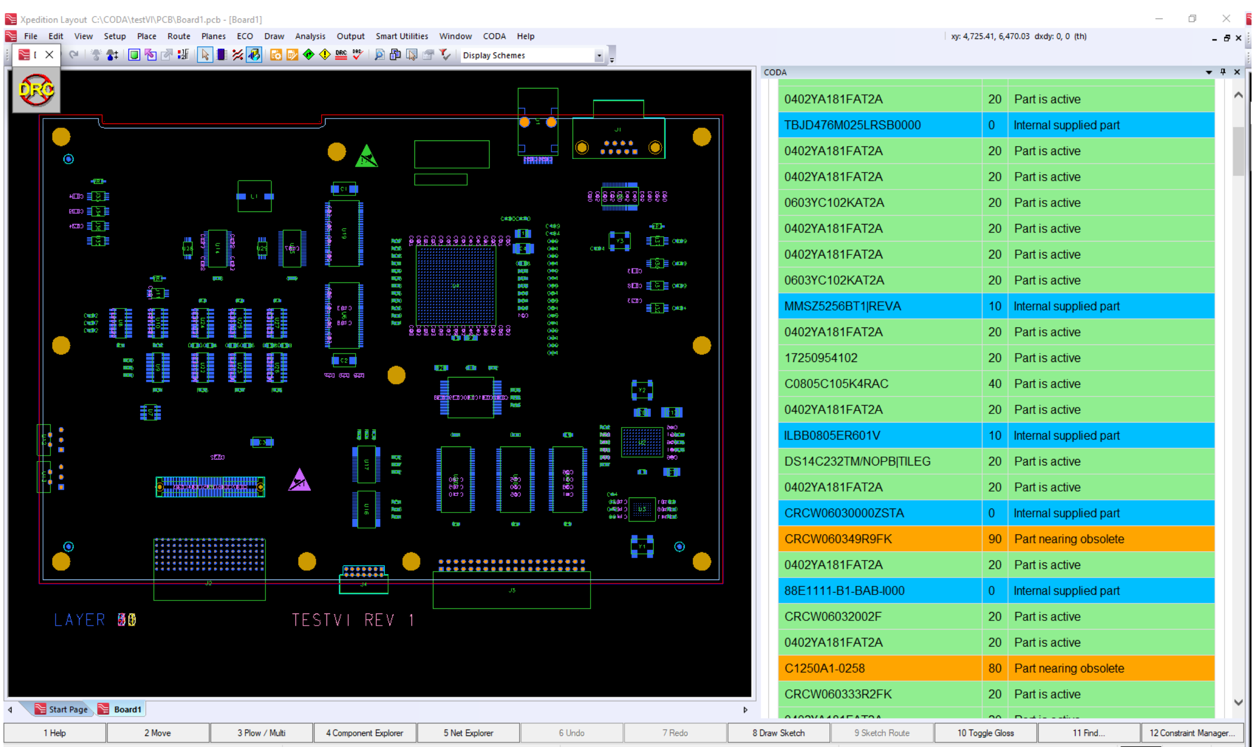


Figure 17: CODA Engineering Workspace View

Distribution Statement A: Approved for Public Release: Distribution Unlimited

The components of CODA provide the end user with the information they need to help make early decisions.

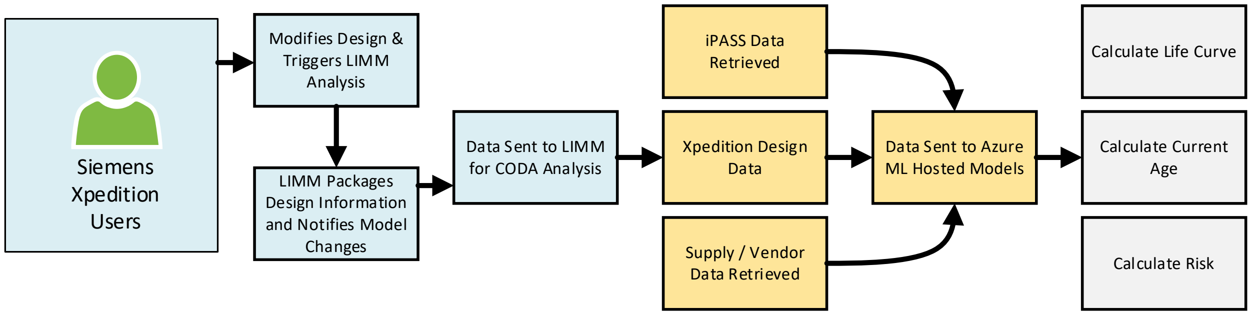


Figure 18: CODA Data / Model Flow

Features & Attributes

CODA consists of the following features that were identified during the requirements analysis:

- Integrated menu to launch CODA within Siemens Xpedition
- User logs into CODA via username and password
- User chooses project and design concept the design represents
- CODA stores the credentials and links the Siemens Xpedition project to LIMM project and design concept
- User can view historical analysis runs
- User can run a new analysis
- User can view analysis run results and view recommended actions or alternative components
- ML models are retrained at intervals as new data flows into the pipeline from internal data and external suppliers

Target Users & Modes of Operation

CODA targets design engineers and obsolescence analyst who leverage the information to assess risk and alternatives for design components. The model results can be used by the analysts directly from the endpoints within Azure. The design engineers will utilize the models through an integration from within Siemens Xpedition's board layout tool.

Software Development/Design Documentation

The team has generated development and design documentation as part of a living document throughout the project. The System Requirement Specification (SRS) documents the requirements and approach the team used. The Software Design Document (SDD) lays out the software design components and approach. These documents are available through MxD or by contacting the team's contact person on the title page.

VI. DISCUSSION & ANALYSIS

Results

The CODA team spent time quantifying the potential impact that CODA would have on the design community including the time spent before CODA analyzing obsolescence risk in electrical components. The team identified approximately 57K man hours spent on obsolescence analysis over the design and manufacturing phases of approximately 200 programs. Through discussions with the SMEs, it is expected that CODA can cover 20-40% of the risk analysis based on the current data provided and can grow as new data gaps are closed and the models are improved with further training and lessons learned.

The table below shows subset of information available though not all vendors and components have access to these fields.

Vendor Provided EOL	Termination Finish	Distributor
Technology EOL	Build to Order	Availability (with history)
UCC Code	Custom Component	Number of Raytheon Projects (with history)
Component Lead Time (with history)	Current Stock	Number of Vendors (with history)
Component Cost (with history)	Vendor Recommended	Component Date

The information is captured using a combination of internal analysis, external sources, and supplier information.

It is critical that data engineering for ML model development provide information in a historical context to understand the overall history of a component's life cycle.

In addition to this information the team identified additional gaps that would improve the obsolescence prediction. These include:

Number of Programs Overall (with history)	Specialized Materials	Industry Utilization – orders grouped by industry
Worldwide Orders (with history)	Sourced Locations	New Technology Readiness
US Orders (with history)	Geo/Political Impact	

It is proposed that an industry wide focus using the same approach as CODA to capture and engineer key data elements that are necessary for life cycle analysis be leveraged to further the accuracy of the analysis. This can be accomplished through an external 3rd party such as a research laboratory or industry institute and be provided to existing members for downstream consumption.

Upon deployment of the developed model, the end user is able to successfully get results based on the current design immediately through a few responses through the Xpedition user interface. This interaction can be found in the provided demonstration video. Once the user has successfully logged into the LIMM integration with Siemens Xpedition, the user has the ability to run a new CODA analysis and view results within minutes. This process would take the user a manual process after concept design was finished to export their component library list in Excel and then manually comparing the data provided in the obsolescence report. This information is now immediately available to the design engineer and can be run at any time with results in minutes. This process will save 100s of hours per program and allows for changes to occur early in the design cycle which the team estimates will lead to a reduction of engineering changes due to obsolescence.

Industry Impact

As we have realized specifically within the last few years, the supply chain can be a bottleneck for all industries. This toolset can be exceptionally useful to the automotive and medical industries. With consistent new and improved designs and the chip shortages seen around the world, these industries that are allowed to source their material internationally will benefit immensely as this toolset will act as a pulse on the supply chain without the need to contact suppliers.

Any government members that are involved with circuit card design and manufacturing and use Siemens Xpedition to do so will be able to utilize this toolset. They will receive the same value throughout the deployment of the toolset that will allow them to analyze their circuit card designs for potentially obsolete components.

The tool can be flowed down through the supply chain as well for system integrators. For systems that include circuit card design and manufacturing, requirements can be flowed to suppliers to provide the output of the toolset. Contractors can require that suppliers use this toolset to analyze their designs and provide the obsolescence probability for the contractor program to realize the supply chain risk.

Progression of the tool can implement more than supply chain information. The scope of the CODA program is to analyze obsolescence. However, the tool can be grown to develop machine learning through performance and other improvements to the design and manufacturing to improve design and mitigate risk.

Key Performance Indicators & Metrics

Table 1: KPI’s and Metrics

METRIC	BASELINE	GOAL	RESULTS	VALIDATION METHOD
System Response	N/A	3-5 Seconds	1-2 Seconds	Timed Test of Actual Functions
Obsolescence Events	Baseline Events / Year	*20% Reduction*	*~20-25%*	*Internal Review of Previous Project*
Component Analysis	.25 Hours / Component	Reduce Effort / Time	Up to $932K / Year	Cost Savings Estimated by Reduction of Manual Risk Assessments

mxdusa.org
@mxdinnovates
info@uilabs.org

1415 N. Cherry Avenue
Chicago, IL 60642
(312) 281-6900

Accessing the Technology

CODA leverages a mix of developed IP through the CODA project alongside background IP through ITI and Microsoft tools. Figure 19 shows the technologies used and network setup for the technologies.

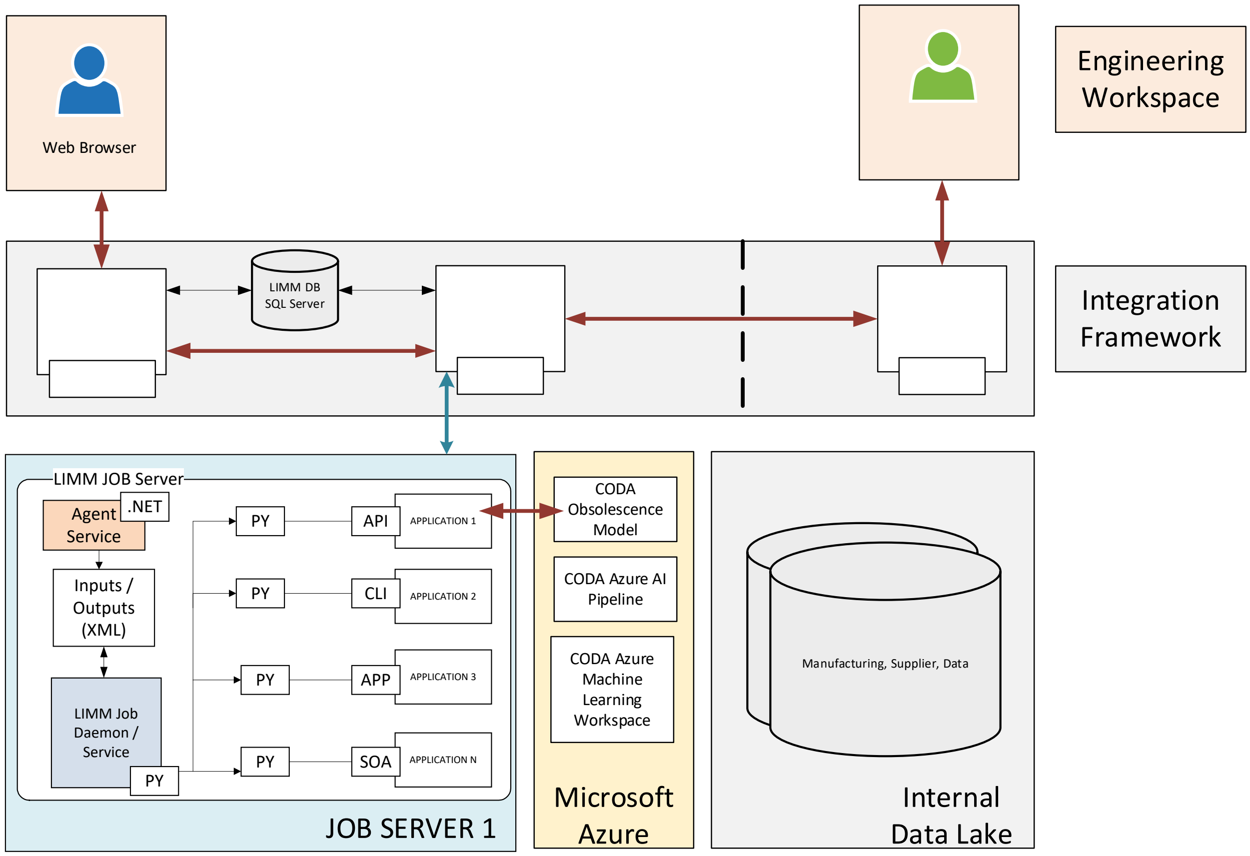


Figure 19: CODA Network and Applications Layers

The engineering workspace is optional frontend for the design to be analyzed. Any interface or tool can be utilized either with a direct connection or a link through the integration framework. To utilize the Xpedition connections, the user must either create their own plug-in using sample information provided or licensing the LIMM connector to Xpedition.

The integration framework and job services leverage ITI's LIMM enterprise software environment. LIMM can be licensed through ITI and provides the out of box connectivity, storage, and linkages required to integrate and store the information provided from CODA analysis.

The Machine Learning model development utilizes Microsoft Azure Machine Learning Workspace environment and development tools. In our demonstration we use a combination of physical hardware, virtual machines on premise, cloud services and storage accounts, and hosted endpoints.

As CODA utilizes all of these in a plug and play approach, other technologies can be utilized such as other cloud services, other design platforms, and other mechanisms that provide knowledge base and integrations to the underlying tools.

MxD members can access any of the scripts, applications, and instructions for setting up the CODA environment. If interested in implementation please reach out to Kris Hill (kris.hill@iti-global.com) at ITI. Delivered scripts represent the demonstration environment so additional details can be discussed regarding LIMM implementation, cloud deployment, or other requirements.

Workforce Development

The team did not specifically address workforce development within the project scope however it was identified that while AI/ML advances are promising and gaining a lot of attention in industry, the models are only as good as the data that drives them. It is essential that industry workforce begin now to understand how data today can lead the industry AI revolutions of tomorrow. Capturing manufacturing, field, and design data holistically across the complex ecosystem or various vendors, suppliers, OEMs, and customers remains an open area that must be addressed with a workforce that understands the value added through capturing real-time and historical data in ways that can be accessed and linked.

Lessons Learned

During the project, the team identified several areas that provided challenges to the project team which either required additional work not fully realized in the proposal or were not as matured to be leveraged out of the box.

Although Azure is a powerful tool to create scalable machine learning solution, it required a steep learning curve for the project team. To alleviate this learning curve, the project team suggests to take the Azure Fundamentals and Solution Architect courses and certifications. This will help the user understand how to securely connect services, cost optimization, and selecting the best technical approach and services out of over 100+ service offerings available on the platform.

The team provided Microsoft beta testing for the Python SDK Machine Learning Libraries within the GovCloud environment. There were cases where the model training documentation was updated while the Team was developing the solution or interfaces being modified during the project execution. Having Microsoft as an advisor to the team was invaluable and provided the team the ability to get direct support to meet the project requirements.

During the project, the team also identified several areas where the supplier fed databases did not fully represent the information required for obsolescence prediction. This provided the team a challenge in working with components that had data represented and was updated by the supplier. During the project the data was refreshed quarterly to ensure the most up-to-date and complete information. To fully predict the component life-cycle some additional information would be helpful however cannot be fully available to a single OEM or supplier.

It is estimated that CODA will be able to provide up to 40% of the data that is currently manually generated through discussions with or reviews of the supplier data to generate obsolescence risk based on discussions with SMEs and a review of the CODA models. The Machine Learning models developed will continue to be trained with new data and refined as additional properties are captured.

The project team proposed the following: "CODA will provide an AI/ML-based circuit card design aid platform that links commercial design tools together with manufacturing cost, life cycle and obsolescence data" and the results have provided the blueprint, framework, process, and the resulting model that represents the obsolescence risk and recommendations.

VII. CONCLUSIONS & FUTURE WORK

CODA will provide Raytheon engineers obsolescence risk scores that are derived from historical and current supplier and internal information using the machine learning models developed. The users will be able to at a minimum see areas of the design that are at risk early within the design tools without the need for external resources or interventions after the design. This is expected to reduce the number of engineering changes due to obsolescence by 20-25% based on the existing data. However, the models are not perfect as they represent a starting point for the obsolescence team to expand on.

Before implementing machine learning based solutions, companies must understand the data requirements and conduct survey and experiments to understand the information they capture, the information required to produce results, and be able to access a large dataset for more accurate results. This will ensure hurdles to the data science are mitigated and provide upfront requirements to capture additional information early in the project.

CODA provides the framework but next steps should provide additional models developed that look at other areas where engineering change can be mitigated through AI and provide assistance to the engineers during design. Eventually these models may even be able to predict and produce the designs directly.

For obsolescence the next steps are to capture a larger industry, supplier, OEM, etc. base of data that can be leveraged for future model development. This includes the attributes identified that would provide more historical data to better predict obsolescence. By linking the data within the larger ecosystem of companies and customers together, everyone would benefit from reduced efforts and costly engineering changes.

Next Steps & Challenges

Immediate next steps for CODA are to educate the industry on the approach, technologies, and integrations that were conducted as part of this project.

The project team proposes the next steps to look specifically at obsolescence is to work with the research laboratory and depot centers that are responsible for obsolescence analysis for delivered and ongoing maintained products. Having access to more historical data, expanded attributes of that data, and the ability to group information based across the defense industry will provide the much needed data that would help not only Raytheon but all defense contractors assess obsolescence risks for both manufacturing and field during design.

The project team proposes an assessment phase to analyze across a larger supply chain base to identify the information required and appropriate ways to access this data from various sources. Providing this technical data as a service to train and develop AI models as services is the future of intelligent platforms that can drive generative designs that truly encapsulate downstream engineering changes. These models can be used throughout the lifecycle in automated processes and become a living artifact of the technical data package for all parts, systems, and deliverables.

The project will be commercialized through ITI's LIMM product suite and available for trial usage by the MxD members. The models will be further developed and transitioned through Raytheon for eventual production usage within the designers.

Transition Plan

The table below provides a catalog of all of the project deliverables and their respective transition routes. Deliverables can transition through deployment at an industry member's site, as an educational reference or through a commercialization effort. Each of these transition routes are detailed below.

Table X: Deliverable Deployment Summary

#	DELIVERABLE FILE NAME	TECHNOLOGY INTEGRATION	EDUCATION	COMMERCIALIZE
1	Engineering Workspace Integration with Xpedition			X
2	LIMM CODA Model Integration Python		X	X
3	CODA Demonstration Pipeline Model Python Code		X	
4				
5				

Engineering Workspace Integration with Xpedition includes the specific add-in that integrates with LIMM and will be provided as a capability within the commercial LIMM application.

The LIMM CODA Model Integration python script provides the scripts used to consume the AI model from the Azure endpoint. It can be used as a template for customization of duplicated work and the basis for the commercialized version of the adapter used for LIMM. Additional security, SSO, and other requirements will be required.

The CODA Demonstration pipeline sample models are the python code used to develop the demonstration within Microsoft Azure. It can be used as a template for customization of duplicated work.

VIII. APPENDICES

Appendix A: Definitions

AI: Artificial Intelligence

ATL: Active Template Library

CCA: Circuit Card Assembly

CODA: Cognitive On-Demand Design Assistant

ECO: Engineering Change Order

KNN: K-Nearest Neighbor

LIMM: Linked Intelligent Master Model (ITI product to automate and link design knowledge)

ML: Machine Learning

PCB: Printed Circuit Board

SME: Subject Matter Expert

SSO: Single Sign On

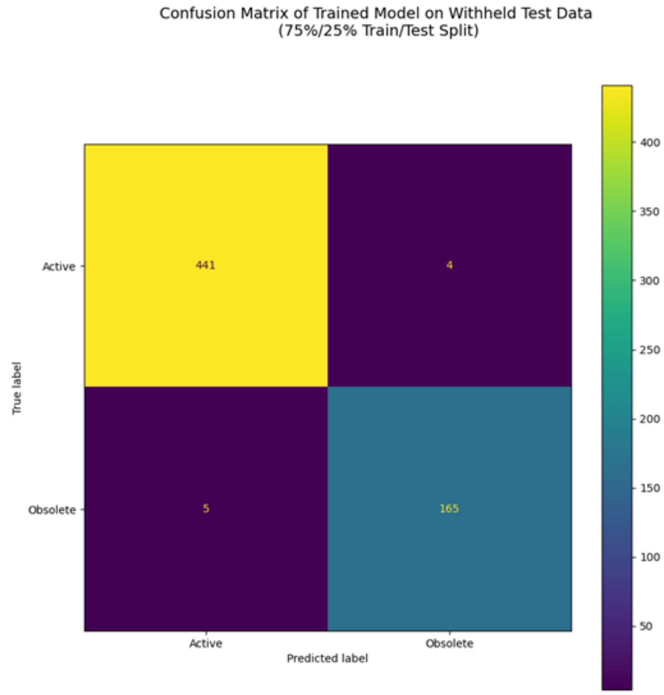
Appendix B: Demos

- Linked Intelligent Master Model version 6.0
- Siemens Xpedition Layout v2.11
- Microsoft Azure Machine Learning Studio

A video demonstration is provided as a deliverable to the project. For LIMM pre-requisite and instructions please refer to ITI for the latest supported documentation and trial licenses.

Appendix C: Validation & Testing

To validate the results from the machine learning model after training, the component data was randomly split into 75% training data and 25% test data. The machine learning model along with the feature functions (Ordinal encoder, Standard scaler and Imputer) were all trained on the training data. Then the model's performance was evaluated on the withheld test data. The confusion matrix below shows the test results.



The results show that there was low number of misclassifications, especially the expensive miscalculations of obsolete components being predicted as active.

The recommendation system was not tested within the scope of this study. Funding for a fully productionized solution needs to be in place to test the feasibility of the component recommendations by collecting feedback from the design engineers. In the long run, a collaborative-filtering approach will be used in the productionized solution to provide a recommendation using a combination of the parametric values along with the design engineer community knowledge.