Public Quarterly Report

Date of Report: 7th Quarterly Report-April 30, 2020
Contract Number: 693JK31810001
Prepared for: DOT
Project Title: Improvements to Pipeline Assessment Methods and Models to Reduce Variance
Prepared by: GTI
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For quarterly period ending: April 30th, 2020

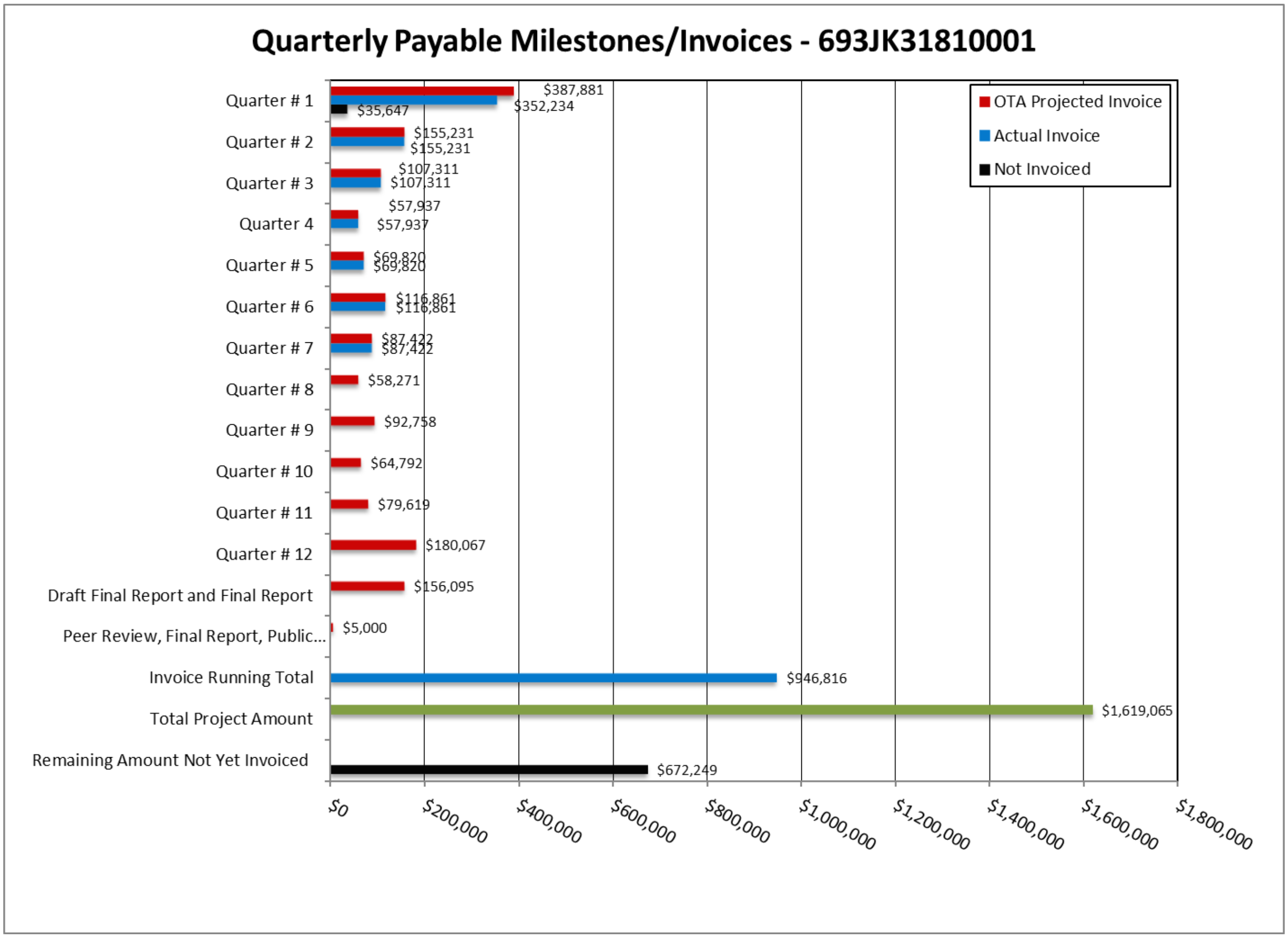
1: Items Completed During this Quarterly Period:

Item #	*Task #*	*Activity/Deliverable*	*Title*	*Federal Cost*	*Cost Share*
47	3.2.2.3	Uncertainty Reduction	Probabilistic Fracture Assessment Phase 5 Report	$8,345	$ -
48	3.3.1.1	Uncertainty Reduction	Integrated Variance Reduction and Bayesian Updating Phase 1 Report	$10,000	$ -
49	4.2.3	Structural FEM Study	FEM DoE Phase 5 Report	$4,908	$ -
50	5.2.2.3	FEM Simulation of NDE Signal Responses	Model-based Framework Phase 5 Report	$10,000	
51	5.3.1.1	FEM Simulation of NDE Signal Responses	Learning and Data Fusion Phase 1 Report	$10,501	
52	6.2.2	Data analysis	3rd Data Analysis Methods Progress Report	$32,650	$ -
53	9.2.3	Project Management	7th Quarterly Report	$1,018	$ -

2: Items Not Completed During this Quarterly Period:

Item #	*Task #*	*Activity/Deliverable*	*Title*	*Federal Cost*	*Cost Share*
NA	NA	NA	NA	NA	NA

3: Project Financial Tracking During this Quarterly Period:



The invoice that will be submitted will include the following line items:

Item #	*Task #*	*Activity/Deliverable*	*Title*	*Federal Cost*	*Cost Share*
47	3.2.2.3	Uncertainty Reduction	Probabilistic Fracture Assessment Phase 5 Report	$ 8,345	$ -
48	3.3.1.1	Uncertainty Reduction	Integrated Variance Reduction and Bayesian	$ 10,000	$ -
49	4.2.3	Structural FEM Study	FEM DoE Phase 5 Report	$ 14,908	$ -
50	5.2.2.3	FEM Simulation of NDE	Model-based Framework Phase 5 Report	$ 10,000	
51	5.3.1.1	FEM Simulation of NDE	Learning and Data Fusion Phase 1 Report	$ 10,501	
52	6.2.2	Data analysis	3rd Data Analysis Methods Progress Report	$ 32,650	$ -
53	9.2.3	Project Management	7th Quarterly Report	$ 1,018	$ -
			Total	$ 87,422	$ -

4: Project Technical Status

The project technical work continues to progress as planned.

The focus in quarters 6 and 7 was to fully align the workflows of ASU, MSU and GTI.

- In quarter 6 we moved to using the same 3D models and the COMSOL Multiphysics modeling platform across all teams.
- In quarter 7 MSU began simulating the defects that ASU and GTI were working on
  - GTI running the structural FEM analysis
  - ASU performing the UQ analyses and dictating the next design point to run in order to minimize uncertainty across the analysis domain
  - MSU simulating MFL and Eddy Current techniques using COMSOL
- At the end of quarter 7 GTI and ASU discussed appropriate data analytics methods with the Principal Investigator of DOT contract 693JK31810003 “Validating Non-Destructive Tools for Surface to Bulk Correlations of Yield Strength, Toughness, and Chemistry” to determine how to best generate useful outputs for the industry from the combined results of these two projects
- The remaining 15 months of this project will be utilized to refine the useful data analytics within the context of the technical deliverables.
- Efforts will be made to streamline data transfer between the projects and investigators

The executive summary from each of the detailed task updates, that appear below, are pasted in this section for convenience.

Item # 47, Task # 3.2.2.3, Uncertainty Reduction, Probabilistic Fracture Assessment Phase 5 Report, Item # 48 Uncertainty Reduction, Integrated Variance Reduction and Bayesian Updating Phase 1 Report

This report summarizes the work done by ASU during the 7th quarter period, which is mainly focusing on the non-Gaussian random corrosion surface simulation and the surrogate model construction to replace the time-consuming finite element model. The deliverable for Task 3.2.2.3 Uncertainty Reduction: Probabilistic Fracture Assessment Phase 5 is completed.

Task 1 non-Gaussian random corrosion surface simulation.
The loss of materials due to corrosion is an important factor that can affect the material properties and working life. It is a naturally occurring phenomenon commonly defined as the deterioration of a material (usually a metal) that results from a chemical or electrochemical reaction with its environment. In the previous report, the corrosion surface is represented by Gaussian random field. However, in nature, most cases are non-Gaussian. And the non-Gaussian random field simulation remains challenging in the open literature. An efficient algorithm for simulating random corrosion surface is developed in this report. The method can well match the first and second-order statistics of the random corrosion surface. And it can handle not only Gaussian cases but also any arbitrary ones. If the experimental data of the real pipeline corrosion surface (loss of materials) is available in the future, this method can be easily applied to characterize an represent the real random corrosion surface.

Task 2 Surrogate model construction by active learning kriging model.
The fully developed finite element model involving the random corrosion surface can be time-consuming, which is not suitable for probabilistic fracture analysis. To reduce the computational efforts, the numerical efficient surrogate model using the active learning kriging model is trained to replace the time-consuming finite element model. Among the countless uncertainties in geometries, loadings, material properties, random corrosion surface, five key factors that are sensitive to the system response are selected to be the surrogate model inputs. For

outputs, three stresses that are critical to the system failure are chosen. Then, each response will be replaced by the surrogate model for further probabilistic fracture analysis.

We also started the perform the investigation for variance reduction. This is the first report for this task and we will continue the investigation in the following several quarters. A general Bayesian network including loading, geometry, materials, and NDE information is presented using Bayesian Network and generic modeling approach is presented. We will add future numerical example and demonstration studies in the future. The deliverables for 3.3.1.1 Uncertainty Reduction: Integrated Variance Reduction and Bayesian Updating Phase 1 Report is finished.

Item # 49, Task # 4.2.3, Structural FEM Study, FEM DoE Phase 5 Report

Task 4.2.3 work focused on developing a workflow for building an FEA-informed surrogate model based on ASU's active learning kriging algorithm and executing a DoE to verify the algorithm. The workflow was successfully established and verified. The DoE used the previously created circumferential-crack and corrosion model and evaluated variations in crack size, depth, and circumferential position together with corrosion depth and axial position. ASU supplied the corrosion depth patterns.

The collaborative work between GTI, ASU, and MSU, is now well established, where GTI is providing the structural analysis execution for ASU's surrogate model development, and the flawed pipe geometry model for MSU's sensor simulations. The model coherence in this collaboration will help develop an understanding the uncertainties in flaw detection and uncertainties in flaw criticality, both of which combine to affect fitness-for-service (FFS) assessment uncertainties.

GTI also conducted a general review of mapping FFS uncertainties as part of the effort to develop a coherent approach that can ultimately tie available field data, existing FFS procedures, and the state-of-the-art in FEM simulation and UQ surrogate models.

Item # 50, Task # 5.2.2.3, FEM Simulation of NDE Signal Responses, Model-based Framework Phase 5 Report, Item # 51, Task 5.3.1.1, Learning and Data Fusion Phase 1 Report

This report summarizes the work done by MSU during this reporting period. To directly address the impact of geometry pipe model designed by GTI. The rationale is that different geometrical design (init/t400/t900) imported from CAD design may be decomposed into different FEM demonstration which reflect pipe corrosion/crack variation in the real life. Each sample included the same pipe geometry at both ends to act as reference positions. Three inspection models were formed to cover application of MFL and Eddy current testing technique. During the 7th quarter, the Task 5.2.2.3 with deliverable, FEM Simulation of NDE signal: Model-based Framework Phase 5 is completed. The Task 5.3.1.1 with deliverable, FEM Simulation of NDE signal: Learning and Data Fusion Phase 1 is also completed in the 7th quarter, while this work has actually been initiated and in progress in earlier quarterly efforts on transfer learning. Experimental work is also initiated during this quarter, in which the MFL models have been validated by our preliminary results using representative flat samples. MSU team is working towards a comprehensive multi-model NDE database for the learning and data fusion tasks, and subsequent uncertainty reduction work.

Item # 52, Task # 6.2.2, 3rd Data Analysis Methods Progress Report

The project team has held multiple discussions on the topic of what would constitute a useful deliverable from the data analytics portion of this project. The current consensus recognized that the available data falls into four broad categories listed below:

Meta Data
Data that is known to the operator to a greater or lesser extent.

- Pipe outside diameter is well known as the pipe is OD controlled
- Wall thickness is known to a lesser extent due to the lack of traceable, verifiable and complete data in some circumstances
- Pressure is well known

These data allow us to calculate the nominal hoop stress in the pipeline

Macro Data
Data that can be gathered from inline inspection of the pipeline

- Crack length
- Crack depth
- Defect type

Mini Data
Data that can be gathered from modern non-destructive evaluation methods about pipe material characteristics

- Yield strength
- Strain hardening exponent
- Strain hardening coefficient
- Toughness
- Chemistry

Micro Data
Data related to the local stress intensification factor in the region of a defect (not at the crack tip). This information allows us to estimate the general local stress field in the region of a defect due to a combination of loading, boundary conditions and pipe geometry

- Local pipe displacements (bending moments)
- Geometry of fittings and appurtenances at the point of interest
- Geometry of local defects such as
    - Gouges
    - Dents

These four categories of data allow us to construct influence diagrams, or hybrid causal models of the stress states in pipe segments that allow us to estimate the criticality of known defects under interacting threats.

Such a hybrid causal model can be used to populate a risk register containing the individual pipe segments (dynamic segmentation), the likelihood of a known flaw becoming critical under a range of boundary conditions and interacting threats. The analysis can generate a confusion matrix for each listed scenario that can inform mitigative actions to be taken.

The hybrid causal models will combine deterministic causality where appropriate and data driven machine learning of parameters governing the output conditional probability tables. The ASU team have provided a sketch of a potential Bayesian network configuration that incorporates the above reasoning. An additional potential model is provided below.

The upcoming four quarters will funnel the research efforts of all three project teams, as well as insights from DOT contract 693JK31810003 “Validating Non-Destructive Tools for Surface to Bulk Correlations of Yield Strength, Toughness, and Chemistry” into a working Bayesian network model capable of supporting the risk register described above.

Item # 53, Task # 9.23, Project Management, 7th Quarterly Report

All project management reporting requirements have been met.

5: Project Schedule –

All deliverables scheduled for completion in the sixth quarter were completed as scheduled.

End Project Status Update