A Smart Sensor Network for Real-Time Monitoring of Piggable and Non-Piggable Gas Transmission Pipelines

A Proposal Submitted To

Oil and Gas Program Solicitation 2005
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1. CRITERION 1 – SCIENTIFIC AND TECHNICAL MERIT

a. Degree to which the proposed technology or methodology represents an important advancement toward achieving the "Research Objectives for this Funding Opportunity Announcement" in the targeted Area of Interest.

As part of the previously funded research project entitled "A Data Fusion System for the Nondestructive Evaluation of Non-Piggable Pipes" (DE-FC26-02NT41648), Rowan University has:

i. Designed and developed neural-network based sensor data fusion algorithms to combine the capabilities of multiple inspection modalities (magnetic flux leakage, ultrasonic, thermal and acoustic emission) for predicting the location, size and shape of gas transmission pipe-wall defects with accuracy and reliability.

ii. Designed and developed validation test platforms for multi-sensor nondestructive evaluation of piggable and non-piggable gas transmission pipelines.

iii. Provided recommendations for effective management of large data sets that result from multiple nondestructive inspections of pipelines.

In the proposed R&D project, Rowan University will expand on previous work by forming an aggressive partnership with industry – specifically, RTD Quality Services and Crane Aerospace & Electronics. We will:

1. Validate previously developed neural-network based pipe-wall characterization algorithms with field inspection data.
2. Develop a smart-sensor wireless network for real-time monitoring of inspection data.
3. Develop a comprehensive knowledge management strategy for determining the optimum inspection interval for piggable and non-piggable pipelines.

Key elements of this proposal specifically address the following research objectives in the funding opportunity announcement:

i. An aggressive partnership with a Research University, a Wireless Communications and Networking Company and the Oil & Gas Industry to ensure transfer of relevant technology.

ii. An effective leveraging of R&D funds among the project partners to improve the state-of-the-art in gas transmission pipeline inspection.

iii. The development of innovative sensor technologies for real-time monitoring and assessment of the transmission pipeline integrity. In the broadest sense, Smart Sensor technologies present the opportunity to improve measurements and provide real-time extraction of information. Measurements are improved through enhancements in the accuracy and confidence of data made possible by local sensor components devoted to quality assurance. Information is extracted from the real-time data stream using embedded algorithms contained within the smart sensor.

iv. The ability to assess the status of both piggable and non-piggable pipelines.

v. A comprehensive knowledge-management strategy to ensure delivery reliability.

b. The degree to which the proposed work identifies and/or makes progress on new concepts.

The combination of existing sensor technologies with intelligence adapted to the pipeline inspection environment provides a uniquely innovative approach. The contribution of the proposed work by embedding portions of the signal processing procedures into the local sensors makes progress toward the ultimate goal of improving the reliability of the natural gas infrastructure.

c. The likelihood of developing a new successful technology.

The smart sensor approach combines proven sensor technologies—e.g., MFL, ultrasound, laser—with maturing sensor architectures defined through a family of new industry standards (IEEE 1451.N). In turn, these are based on proven instrumentation and networking standards. Our previous work with smart sensors, sponsored by NASA, has been focused on the rocket engine test environment, which shares certain critical elements in common with natural gas pipelines including an emphasis on high-reliability measurements and information extraction for real-time evaluation of system state. An added constraint of the propulsion test environment was the additional need for continuous assessment of the health of the smart sensor elements to improve the confidence in the evaluation of the overall system state.

d. The degree to which the proposed work is based on sound scientific and engineering principles.

The proposed smart sensor approach is based on highly-developed and successful open architectures for networking (e.g., IEEE 802.N), which have been reliably incorporated into many generations of communication infrastructure. The emergent IEEE 1451.N series of standards borrow heavily from that model thereby incorporating by reference much of their inherent robustness and reliability. Adopting an open standard ensures that the results of this effort can be used by others; similarly, developments by others to the same standards can be integrated into this evolving work.

e. Anticipated benefits of the proposed work in comparison to current commercial and emerging technologies.

The proposed smart sensor approach is a departure from current commercial practice in that the signal processing is pushed down to real-time assessment within the sensor. This provides the dual benefits of improved analysis response time and the potential for data rate reduction. In addition, the development of capability to wirelessly transmit inspection data to remote host sites for real-time assessment provides for significantly reduced inspection turn-around time.

f. Feasibility of the proposed concept.

The proposed project consists of 3 key elements – the feasibility of each is discussed below:

i. *Validation of previously developed neural-network based pipe-wall characterization algorithms with field inspection data*.

The feasibility of validating neural-network based algorithms that predict the location, size and shape of pipe-wall anomalies is very high because it leverages previously sponsored work DE-FC26-02NT41648. Algorithms tested in laboratory conditions will be subject to staged field tests allowing for the possibility of adaptation to field conditions. The consortium of Gas Pipeline Industry partners allows us to have access to a rich set of field data.

ii. *Development of a smart-sensor wireless network for real-time monitoring of inspection data*.

The feasibility of developing a smart sensor based approach has a high probability for success because it leverages prior work. One of the risk factors affecting feasibility is the size of the algorithms that need to be embedded into a smart sensor. Relatively simple (e.g., < 10,000 lines of code) algorithms can fit into widely available embedded computer architectures; more complex algorithms may have to be partitioned between the smart sensor and the associated host computer.

iii. *Development of a comprehensive knowledge management strategy for determining the optimum inspection interval for piggable and non-piggable pipelin*es.

The feasibility of developing a knowledge management strategy that comprehensively treats current and historical inspection data for determining the optimum inspection interval is high because it leverages our previous work with NASA involving the development of knowledge management tools for integrated systems health management (ISHM). The tool, *G2* (Gensym, Inc.) will be used as the knowledge management framework. We will apply available gateways that we have already developed to interface to external analysis engines such as *MATLAB* (Mathworks, Inc.) for execution of the defect-determining algorithms cited above.

2. CRITERION 2 – APPROACH AND UNDERSTANDING

a. Adequacy and feasibility of the applicant's approach to achieving stated objectives.

The technical approach for meeting each of the proposed project's objectives is described below.

i. Validation of previously developed neural-network based pipe-wall characterization algorithms with field inspection data.

Field data will be obtained from a pipeline industry consortium currently composed of RTD Quality Services and Transcanada Pipelines – efforts will be made to expand this consortium to other industry partners. Laser Profilometry with a Laser Pipeline Inspection Tool (LPIT) will be employed to define a process for calibration and subsequent grading/regrading of in-line inspection (ILI) data for improved accuracy and increased confidence levels. Also, a statistical process for measuring the improvement on a continuous basis shall be developed and defined. The goal for this project is to improve the accuracy and confidence levels associated with ILI data from ±10% with 80% confidence level to ±5% with 90% confidence levels and to develop a comprehensive process for validating the results thus obtained.

A two-stage strategy is envisioned for analyzing MFL signals when LPIT C-scans are available for a set of corrosion anomalies. The heart of this algorithm is the determination of corrosion-profile information contained within the MFL signature that is in common with the same information contained in the LPIT C-scan. Also, one can determine corrosion-profile information that is missing in the MFL signature, but is available in the LPIT C-scan. Results obtained from a pair of artificial neural networks that can be trained to predict these two separate sets of information can be combined to accurately and confidently estimate the true corrosion-profile. The following paragraphs describe this strategy in more detail.

Figure 1 illustrates the varying information contained within signatures that result from multiple inspections of the same corrosion anomaly. Both MFL and the LPIT C-scan contain information about the "true" corrosion-profile. (In fact, it is assumed that the LPIT C-scan contains almost ALL of the information regarding the corrosion-profile – however, this information is shown separately in Figure 1 for illustration purposes). The central region, where the three circles intersect represents *redundant* information in the MFL and LPIT signatures. In other words, this is the corrosion-profile information contained within the MFL signature that is identical to that within the LPIT signature. The *complementary* information shown in Figure 3 is that corrosion-related information contained in the LPIT signature that is *not* contained in the MFL signal. A complete estimate of the true corrosion-profile can be made by the combining the both redundant and complementary information.

The proposed approach for predicting corrosion profiles from MFL signals, shown in Figure 2, uses the concept of redundant and complementary information described above. Two separate artificial neural networks are designed – one is trained to predict that information in the MFL signature that is also present in the LPIT C-scan; the other is trained to predict information in the MFL signature that is present *only* in the LPIT C-scan. By dividing the problem into two explicitly separable problems, the neural networks can be trained separately. It is anticipated that the first neural network that predicts redundant information is easier to train, since it primarily operates as an interpolator. The corrosion-profile regions predicted by this network can be treated with confidence. The complementary network performs as a trained extrapolator – the combined predictions increase the accuracy of the corrosion-profile estimate. Since multiple intermediate estimates are used in arriving at a final estimate of the corrosion-profile, it is anticipated that small perturbations in signal amplitude matrices will not adversely affect the final prediction – a problem that is present in "brute-force" approaches for training neural networks.

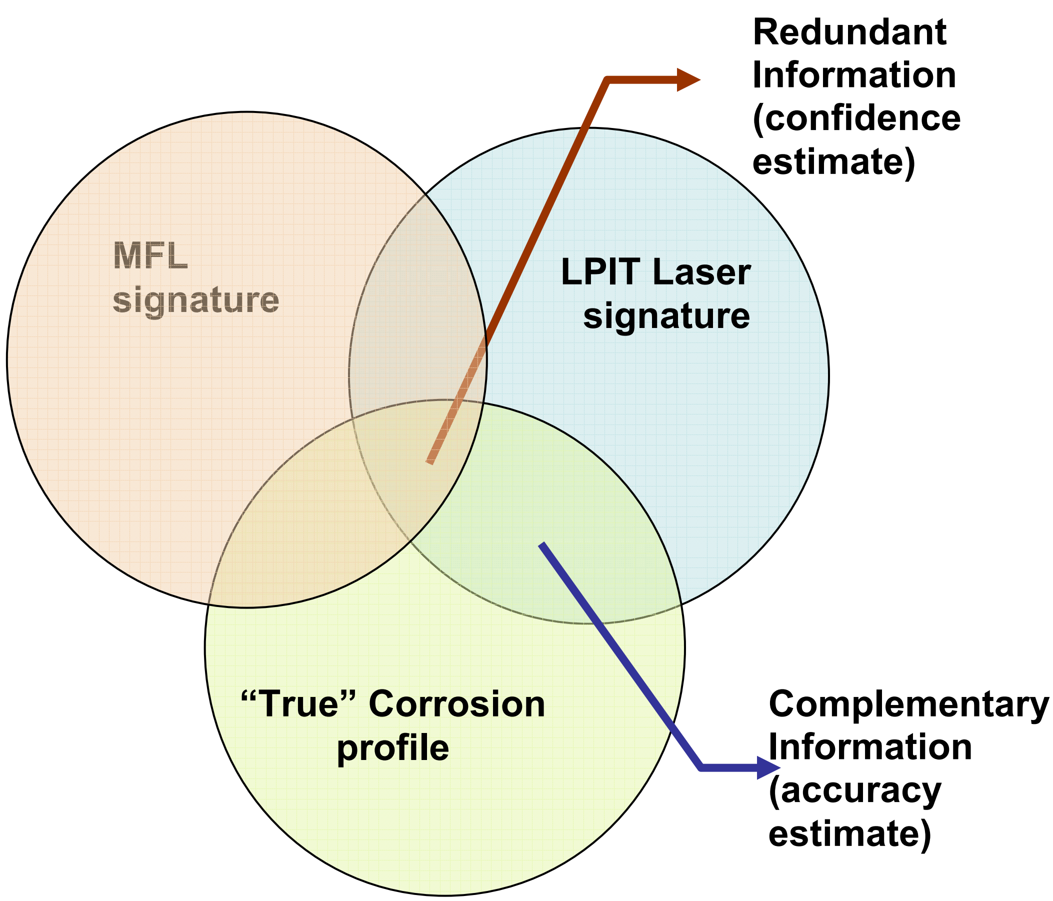

Figure 1: Illustrating redundant and complementary information present in NDE signatures.

Although the signal characterization technique is described in this section with respect to corrosion anomalies using MFL data in piggable pipelines, our previous work under DE-FC26-02NT41648 has shown that a similar technique can be used for inspecting non-piggable pipelines using acoustic emission methods.

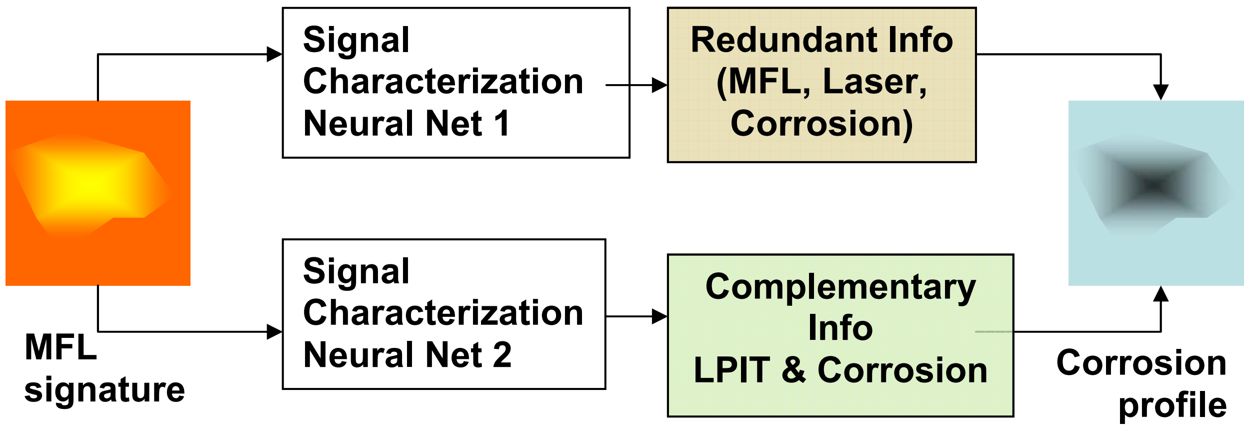

Figure 2: Proposed MFL signal characterization approach for predicting corrosion profiles.

ii. Development of a smart-sensor wireless network for real-time monitoring of inspection data.

The smart sensor development approach will consist of:

- identifying candidate sensors,
- evaluating the suite of signal processing algorithms currently available for both single- and multi-mode sensors,
- evaluating the cost-benefit associated with each algorithm to find the optimum set for embedding,
- mapping the selected suite of algorithms into model smart sensor architectures, and
- evaluating the performance of the complete smart sensor in a simulated pipeline inspection environment.

The general smart-sensor model is shown in Figure 3, which is based on our earlier NASA project work. This model applies to a wide range of complex systems.

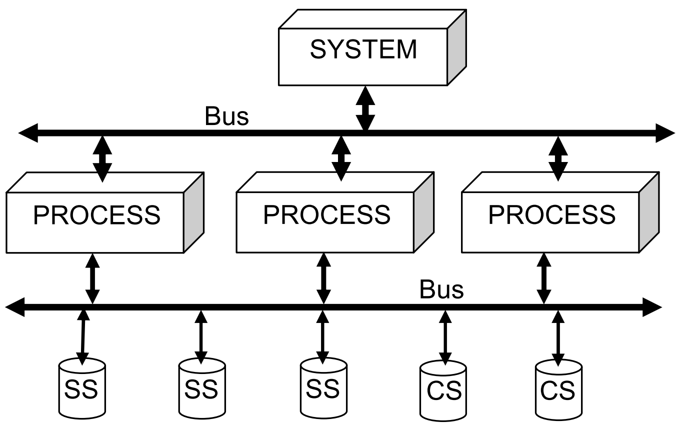

Figure 3: The Integrated System Health Management (ISHM) model consists of collections of smart sensors (*SS)* and conventional sensors (*CS*), which are organized into associated virtual *process(es)*; the collection in turn comprises a *system*. Intelligence in support of health management is distributed across all elements. Data and health information is exchanged over *bus(es)*.

In general, such a system collects data from a multitude of sensors, analyzes that data to develop information and delivers results with validity and reliability appropriate to the application. One of the key enabling technology elements are smart sensors and a framework of supporting intelligence (see iii.).

Smart sensors assume a significant role in these architectures. A smart sensor shares similarities with a "non-smart" or "conventional" sensor in that they both produce measurement data; the smart sensor differs because it also possesses sufficient computing power to perform algorithmic assessment of its state to inform higher-level process(es) of the estimated quality of the data, of the ability of the smart sensor to perform its functions, and can also perform a collection of algorithms for information extraction and data compression. Figure 4 shows an example smart sensor architecture.

Intelligent sensors have other challenges including the need for novel total-system calibration methods to address the distributed voltage reference problem (i.e., every smart sensor has an individual voltage reference compared to the conventional data acquisition model where one—or few—high accuracy references are shared). Similarly, methods are required to provide clock synchronization protocols for improving time references between sensors.

The general organization of the interface between a smart sensor and the higher-level intelligence is based on extension to recent smart transducer standards [IEEE 1451.N series]. Our previous innovation is the addition of a health electronic data sheet (HEDS) to complement the transducer electronic data sheet

(TEDS). For the first time, a smart sensor contains not only a description of its basic measurement functions (TEDS), but also descriptions of its health assessment capabilities and basic fault parameter set.

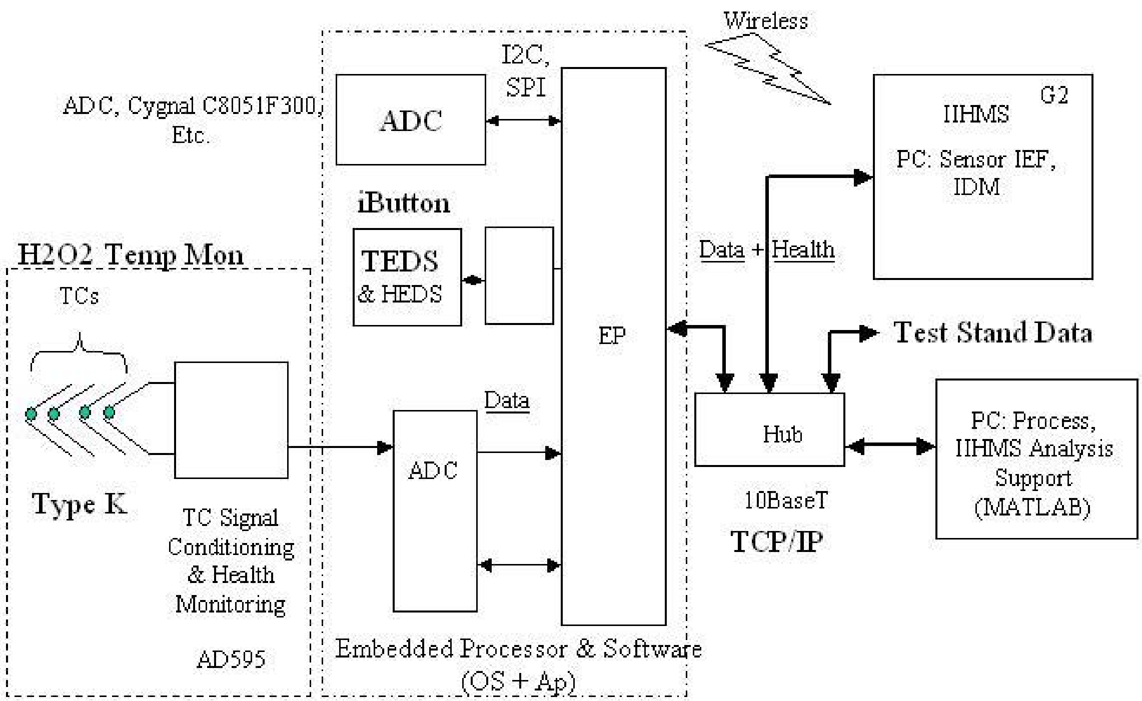

Figure 4: Example smart sensor architecture.

The ultimate goal of this work is to construct a wireless network that interfaces with the smart sensor topologies and is tailored to the needs of pipeline monitoring. In the first phase, the sensor network will be analyzed in order to develop a realistic offered traffic model. Each transducer will be characterized so that the data it provides, and the rate that is needed, is well understood. Using these inputs, simple source encoding algorithms will be developed so that over-the-air traffic can be minimized.

Wireless topologies will be developed to handle this offered traffic. The traffic will be analyzed to determine both peak and average conditions. The necessity, if any, for store-and-forward techniques will be derived. The ability to handle alarm conditions, the expected latency between data generation and data reception, the need for relay stations, and composite system throughput will be analyzed.

In the second phase, we will construct 5 prototype nodes wireless nodes and select the specific transducers to be used. Further, we will develop a power-supply scheme and prototype it. We will also construct interfaces between the selected transducers and the wireless nodes. We will show that simulated traffic can be successfully passed in a laboratory environment. We intend the wireless nodes be purchased off-the-shelf. A board will be developed to mate transducers to the wireless nodes. This board will also allow us to input simulated transducer data using a PC as the source, not an actual transducer.

In the third phase, we will package the five nodes, and transport them to a real pipeline instrumented with real transducers. We demonstrate that data can be transported with low latency for further signal processing.

We anticipate prototype-testing the wirelessly networked smart sensor topologies for both piggable pipes inspected using the MFL method (the data is transferred at the conclusion of the pigging operation) and non-piggable pipes inspected using the acoustic emission method (in which case, the data can be transferred in real-time).

iii. *Development of a comprehensive knowledge management strategy for determining the optimum inspection interval for piggable and non-piggable pipelines*.

Figure 5 shows the general organization of a complex knowledge bases and the information exchange between the core elements. Knowledge bases appropriate for the three layers of the architecture have to be refined to incorporate component specifications, behavioral models (analytic, empirical, and qualitative), test requirements, expert observations, facility operation history, and other items. The framework will be enhanced by interfaces to humans and other autonomous systems. Visualization tools will help present the condition of the system and provide context sensitive information at the proper level of detail.

The framework also manages context to properly analyze the condition of each element in the system (sensors, components, and processes), as part of defect assessment—i.e., *Event conditioned on Context*. We believe that this fundamental pairing is one of the cornerstones for successful knowledge-based implementations. Combining events with context allows differentiation between behaviors that are healthy in one context but would signify a failure in another. For example, in a distribution pipeline anticipated pressure variations and associated failure modes are different from those encountered in transmission pipelines.

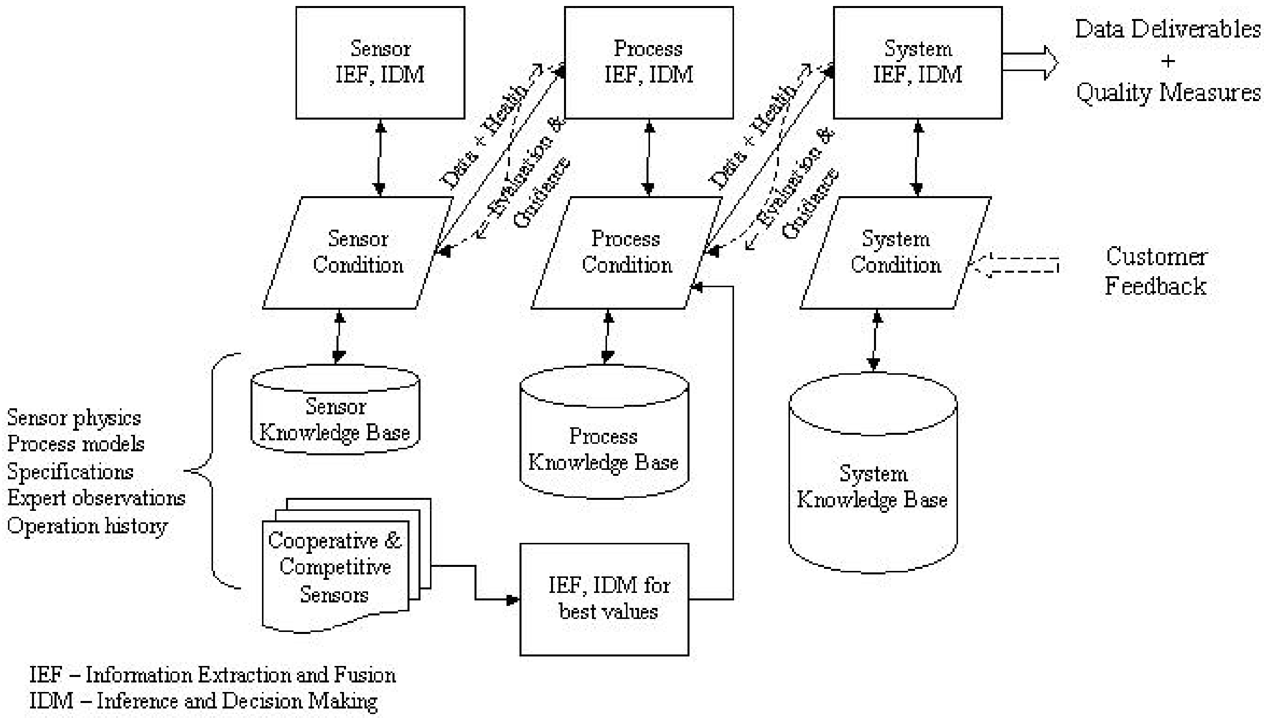

Figure 5: Model of intelligent system showing interplay of data and health flows between elements.

One of the key challenges of knowledge-intensive applications is the methodologies used to organize and access the large arrays of data and knowledge. One element is a nearly linear scaling: The total amount of data that is collected over time can be approximately estimated. The most difficult component is the required evolution of the associated knowledge management—the intelligence—associated with the application. This is of critical importance to ensure that maximum value is obtained from the data sets available. Defect detection algorithms are developed based on the best available knowledge and experts available at a given time. However, as time progresses, new data sets and new instances of anomalies will be detected. It is imperative that each new instance be effectively integrated into the knowledge base. The most inefficient, brute-force approach requires wholesale redevelopment of the defect detection algorithms. However, this is extremely time consuming and suboptimal. As part of DE-FC26-02NT41648, we have developed algorithms for incremental learning and adaptation that offer realistic methods for continuously updating and improving the knowledge base—and most importantly, continuous improvement of detection algorithms.

b. Adequacy of the applicant's understanding of the "Research Objectives for this Funding Opportunity Notice."

This proposal specifically addresses the research objectives for Area of Interest 4 – Delivery Reliability for Natural Gas, to “develop and integrate innovative sensors to provide enhanced assessments of the status of transmission facilities.” In addition, the methods described “include sensors to provide status assessments of non-piggable pipes.”

c. Extent of prior use, research, development or application of the proposed technology and appropriateness of how the prior work relates to the proposed application of the technology.

Previous work that is related to the proposed project’s 3 key elements is discussed below:

i. Validation previously developed neural-network based pipe-wall characterization algorithms with field inspection data.

As mentioned in the beginning of this proposal, as part of DE-FC26-02NT41648), Rowan University has:

- Designed and developed neural-network based sensor data fusion algorithms to combine the capabilities of multiple inspection modalities (magnetic flux leakage, ultrasonic, thermal and acoustic emission) for predicting the location, size and shape of gas transmission pipe-wall defects with accuracy and reliability.
- Designed and developed validation test platforms for multi-sensor nondestructive evaluation of piggable (magnetic, ultrasonic and thermal) and non-piggable (acoustic emission) gas transmission pipelines.
- Provided recommendations for effective management of large data sets that result from multiple nondestructive inspections of pipelines.

As part of this previous project, combinations of UT, MFL, thermal imaging and AE NDE data have been fused to predict defect depths in the range of 0.01” – 0.03” for pipe-wall specimens of thicknesses 5/16” – 1/2”. The accuracy and confidence of the prediction varies in proportion to the information content of the NDE method used for interrogation – for example, MFL-UT combination show higher levels of accuracy than MFL-Thermal combinations. redundant and complementary information related to the location and size of a pipe-wall defect was predicted using homogeneous data combinations that include UT-MFL, UT-thermal imaging and MFL-thermal imaging; the heterogeneous data combination includes UT-AE.

It is the goal of the data fusion neural network to interpolate the redundant and complementary information as well as the intensity of the defect region. To perform this operation the neural network must be trained in the difference between redundant and complementary information. Therefore it is necessary to develop a definition that defines redundant and complementary information for multi-sensor NDE data in terms of the defect geometry. Figure 6 illustrates the definition of redundant and complementary information used in the exercise of the data fusion algorithms.

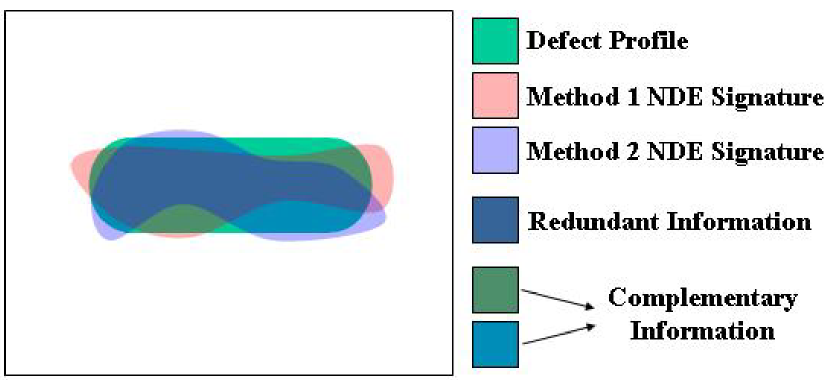

Figure 6: Redundant and complementary data definitions between two NDE signatures.

Pixel gray values are assigned corresponding to the depth of the defect at that location. Complementary information in two NDE images are defined as those distinct pixels in each of the NDE signatures that are present in the defect region, but are not shared between them. Redundant information in two NDE images are defined as those common pixels that are present in both NDE signatures and are also present in the defect region.

Figure 7 illustrates a typical application of this approach for fusing MFL and UT data – the first row shows raw images, the second row shows the redundant and complementary information (pixel color related to defect depth) predicted by the neural network and the third row shows the desired information that the network should correctly predict. The close match between the second and third rows demonstrates the effectiveness of the algorithm for predicting the size and shape of pipe-wall anomalies.

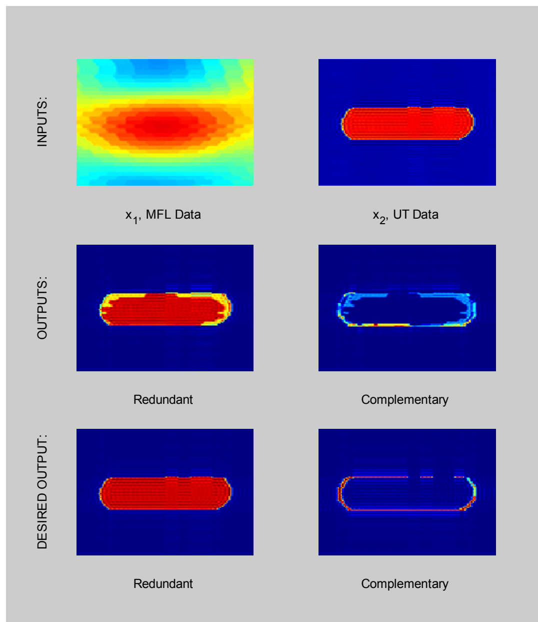

Figure 7: Prediction of redundant and complementary information by fusing MFL and UT signatures obtained from a slot-shaped anomaly.

We have attempted to exercise the proposed pipe-wall characterization algorithm on a small set of LPIT and MFL data obtained from inspecting a section of a real pipeline. Preliminary results for a typical pipe-wall corrosion feature are indicated in Figure 8.

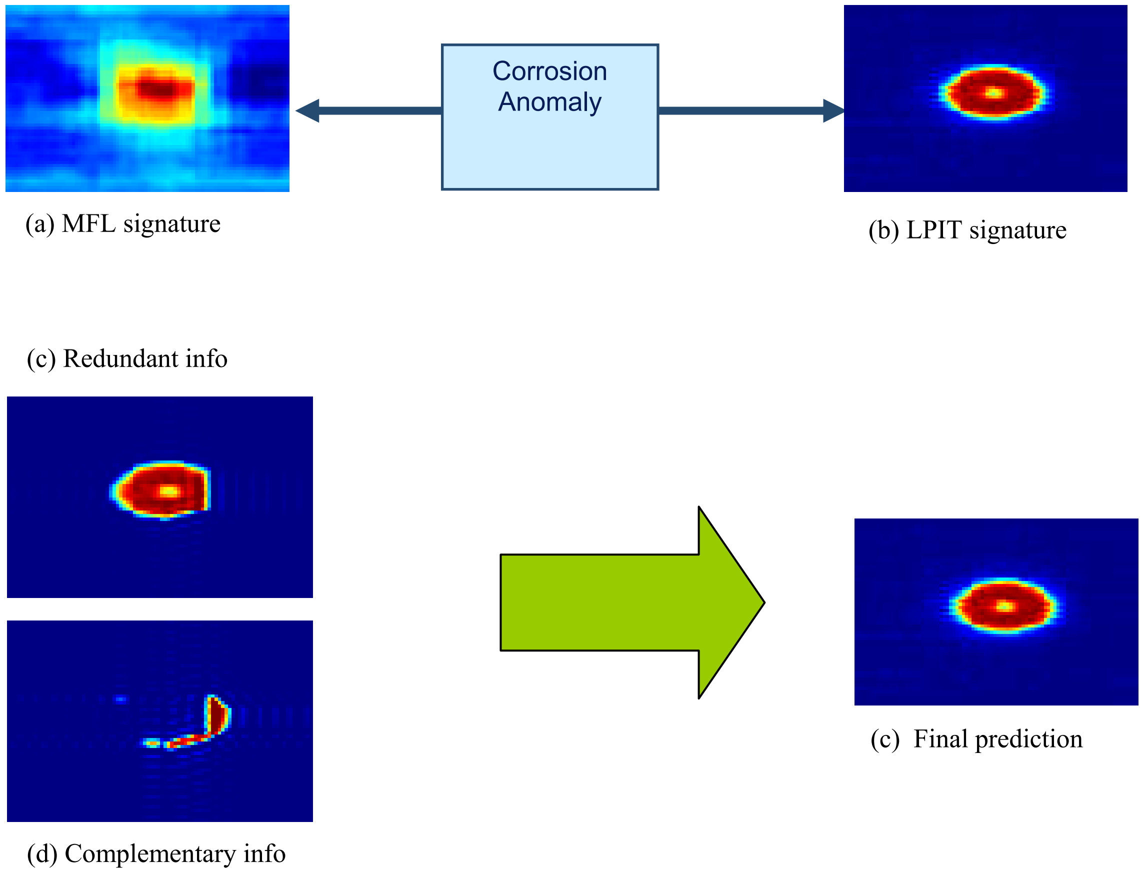

Figure 8: Prediction of redundant and complementary information from MFL and LPIT signatures obtained from a real corrosion anomaly.

ii. *Development of a smart-sensor wireless network for real-time monitoring of inspection data.*

The smart sensor approach we have selected for the proposed work is based on available industry standards (IEEE 1451.N). Our previous work with smart sensors focused on the rocket engine test environment, which shares certain critical elements in common with natural gas pipelines including an emphasis on high-reliability measurements and information extraction for real-time evaluation of system state. The prior application and the proposed work share common features of requiring enhanced sensor data and the concurrent need to process it against performance criteria and make decisions based on the outcomes.

iii. *Development of a comprehensive knowledge management strategy for determining the optimum inspection interval for piggable and non-piggable pipelines* .

Our previous work with NASA related to the development of integrated system health management systems underscores the major problem areas and the critical technologies that need to be matured to address gas transmission pipeline monitoring. These include:

- Mature software environment using knowledge tools to store and manipulate intelligence of nominal and off-baseline behavior with determination of system performance impacts.
- Feature extraction and classification to reliably identify anomalous behavior based on expert experience combined with models (analytic, numerical, statistical, qualitative, and others). Maintenance of knowledge bases to include evolution as part of continuous system performance improvement.
- Exchange of context-sensitive knowledge, data, and health information between elements of a system.
- Distribution of health intelligence across multiple elements.
- Methods for presenting analysis outputs to users.
- A validation testbed with a well defined baseline appropriate to a wide spectrum of technologies to ensure portability.

d. Appropriateness, rationale, and completeness of the proposed Statement of Project Objectives.

Please see following page for STATEMENT OF PROJECT OBJECTIVES (SOPO).

STATEMENT OF PROJECT OBJECTIVES (SOPO)

TITLE OF WORK TO BE PERFORMED: Smart Sensor Network for Real-Time Monitoring of Piggable and Non-Piggable Gas Transmission Pipelines

A. OBJECTIVES

The objectives of the proposed R&D project are:

1. Validation of previously developed neural-network based pipe-wall characterization algorithms with field inspection data.

   Phase I: Identification of field data with simple defect geometries; design, test and validation of the neural network algorithms.

   Phase II: Identification of field data with more complex defect geometries; design, test and validation of the neural network algorithms.

   Phase III: Partitioning of the neural network algorithms between top-level host and smart-sensor platforms.

2. Development of a smart-sensor wireless network for real-time monitoring of inspection data.

   Phase I: System engineering of wireless smart-sensor network including transducer characterization, network protocol development, and development of smart sensor architecture.

   Phase II: Design and development of smart sensors and the wireless node interface including provisions for embedding intelligence and algorithm suite.

   Phase III: Embedding evaluation algorithms; integration into overall architecture; demonstration of the wireless network smart-sensor platform.

3. Development of a comprehensive knowledge management strategy for determining the optimum inspection interval for piggable and non-piggable pipelines.

   Phase I: Development of an anomaly database for piggable and non-piggable pipes.

   Phase II: Development of a hierarchical knowledge management architecture including partitioning of algorithms between top-level host and smart sensors.

Phase III: Integration of smart sensor elements with suite of detection algorithms; demonstration of the complete architecture including wirelessly networked smart-sensors for assessments of pipe-wall integrity in piggable and non-piggable pipes.

B. SCOPE OF WORK

The scope of work required to realize the objectives of the proposed R&D project are shared between the two principal partners - Rowan University and Crane Aerospace & Electronics; RTD Quality services will lead efforts in providing access to real pipeline data that is necessary for system validation. Rowan University will adapt the neural network based pipe-wall characterization algorithms and develop the standards-based smart-sensor network. Crane Aerospace & Electronics will take the lead in developing the wireless data transfer protocol. Rowan University will interact extensively with the Gas Pipeline Industry through RTD Quality Services for the development of the knowledge management model – the overall objective for all these efforts is to arrive at a comprehensive prediction of the optimum inspection interval.

C. TASKS TO BE PERFORMED

PHASE I

Task 1.0 – Research Management Plan

As required by the solicitation, we will develop a work breakdown structure and supporting narrative that concisely addresses the goals of the overall project – detailed schedules, planned expenditures with all major milestones and decision points will be provided.

Task 2.0 – Validation of neural-network based pipe-wall characterization algorithms

Subtask 2.1 – Performing statistical analysis of the data sets obtained from ILI and the LPIT systems to quantify the certainty and confidence levels.

Subtask 2.2 – Selecting a set of naturally occurring external corrosion samples with comparatively simple geometries.

Subtask 2.3 – Collecting the MFL and corresponding profile data for the samples.

Subtask 2.4 – Design, test and validation of the neural network algorithms.

Subtask 2.5 – Performing quantitative assessment for measuring the improvement in certainty and estimation of its effect on the reliability of the data.

Task 3.0 – Development of a smart-sensor wireless network

System engineering of wireless smart-sensor network including transducer characterization, network protocol development, and development of smart sensor architecture.

Subtask 3.1 – Transducer evaluation to determine bandwidth and data characteristics.

Subtask 3.2 – Network architecture evaluation to determine optimum structure for wireless communication between smart sensor nodes.

Subtask 3.3 – Development and evaluation of smart sensor architectures to support networking requirements and embedding of algorithms.

Task 4.0 – Development of a knowledge management strategy

Development of an anomaly database for piggable and non-piggable pipes.

Subtask 4.1 – Analysis and cataloging of key defects.

Subtask 4.2 – Construction of a core anomaly database merging anomalies with example data sets from pipeline inspection data.

Subtask 4.3 – Application of anomaly database to simple defect detection algorithms.

PHASE II

Task 1.0 – Validation of neural-network based pipe-wall characterization algorithms

Subtask 1.1 – Selecting a set of naturally occurring external corrosion samples with more complex geometries.

Subtask 1.2 – Collecting the MFL and corresponding profile data for the samples.

Subtask 1.3 – Design, test and validation of the neural network algorithms.

Subtask 1.4 – Performing quantitative assessment for measuring the improvement in certainty and estimation of its effect on the reliability of the data.

Task 2.0 – Development of a smart-sensor wireless network

Design and development of smart sensors and the wireless node interface including provisions for embedding intelligence and algorithm suite.

Subtask 2.1 – Detailed smart sensor data acquisition design and development to support key transducers.

Subtask 2.2 – Detailed smart sensor digital signal processing development that supports important classes of embedded evaluation algorithms.

Subtask 2.3 – Detailed smart sensor prototype development that includes results of subtasks 2.1 and 2.2 and combines power supply design and wireless communication interface in a fieldable package.

Task 3.0 – Development of a knowledge management strategy

Development of a hierarchical knowledge management architecture including partitioning of algorithms between top-level host and smart sensors.

Subtask 3.1 – Development of architecture to support partitioned intelligence between high-level host processing and distributed smart sensor nodes.

Subtask 3.2 – Expansion of anomaly database to include complex defect detection algorithms.

PHASE III

Task 1.0 – Validation of neural-network based pipe-wall characterization algorithms

Subtask 1.1 – Testing, refining and validating the algorithms for application to various different scenarios and configurations of data sets and pipeline systems.

Subtask 1.2 – Adaptation of the neural network algorithms to the smart sensor topology.

Task 2.0 – Development of a smart-sensor wireless network

Embedding evaluation algorithms; integration into overall architecture; demonstration of the wireless network smart-sensor platform.

Subtask 2.1 – Modification and adaptation of evaluation algorithms for embedding in the smart sensors.

Subtask 2.2 – Integration of the completed smart sensor into the overall architecture.

Subtask 2.3 – Demonstration and evaluation of the completed wireless smart sensor architecture.

Task 3.0 – Development of a knowledge management strategy

Integration of smart sensor elements with suite of detection algorithms; demonstration of the complete architecture including wirelessly networked smart-sensors for assessments of pipe-wall integrity in piggable and non-piggable pipes.

Subtask 3.1 – Integration of smart sensors with complete inspection evaluation architecture.

Subtask 3.2 – Laboratory demonstration of complete inspection evaluation architecture.

Subtask 3.3 – Demonstration of complete inspection architecture that includes selected field-installed smart sensor elements.

D. DELIVERABLES

Project deliverables over the 3-year duration will include all required technical reports.

E. BRIEFINGS/TECHNICAL PRESENTATIONS

Detailed briefings will be provided as requested by the DOE.

e. Adequacy of the proposed project schedule, staffing plan and planned travel.

Each of the three key objectives of this project is divided into three phases – and each phase is planned to last 1-year. There are three faculty at Rowan University supervising this project – Dr. Mandayam will lead efforts in validation and knowledge management, Dr. Schmalzel will supervise the design and development of the smart sensor network and Dr. Polikar will provide expertise in evolutionary and incremental learning neural network algorithms. Our collaborator, Crane Aerospace & Electronics will lead efforts in the design and development of the wireless communications topologies. Also, three graduate students at Rowan University are assigned to the project. In addition, the graduate students will be assisted by Junior- & Senior-level undergraduate student teams as part of the project-based Rowan Engineering Clinic sequence. Travel is planned for annual conferences (Natural Gas Technologies Conference and Review of Progress in Quantitative NDE), field visits for data collection and required periodic visits to the National Energy Technology Laboratory in Morgantown, WV for project briefings to DoE personnel.

3. CRITERION 3 – TECHNICAL AND MANAGEMENT CAPABILITIES

a. Credentials, capabilities and experience of key personnel.

The Principal Investigator in this proposed project is Dr. Shreekanth Mandayam's and the Co-Principal Investigators are Dr. John L. Schmalzel and Dr. Robi Polikar, all from the Electrical & Computer Engineering department at Rowan University, Glassboro, New Jersey. Our principal collaborator (subcontractor) is Advanced Integrated Systems Division (AISD) is part of the Aerospace & Electronics segment of Crane Company of Stamford, Connecticut.

Principal Investigator: Professor Shreekanth Mandayam's (Ph.D. 1996, Iowa State University) professional experience and interests are in the field of digital signal/image processing, artificial neural networks and advanced visualization (virtual reality), applied to nodestructive evaluation (NDE). Dr. Mandayam directs the multi-diciplinary NDE laboratory which contains state-of-the-art imaging facilities - magnetic, ultrasonic, acoustic, thermal, X-ray and optical techniques are supported. Research sponsors in the laboratory include the National Science Foundation, US Department of Energy, US Navy, American Cancer Society, ExxonMobil, Thomson Consumer Electronics, etc. Dr. Mandayam teaches undergraduate courses in engineering electromagnetics and electrical communications systems and graduate courses in digital image processing, artificial neural networks and digital communications.

Co-Principal Investigator: Professor John L. Schmalzel (Ph.D. 1980, Kansas State University) has worked in the area of instrumentation of 30 years. He is an executive officer in the IEEE Instrumentation & Measurement Society and organizes the annual Sensors for Industry Conference. More recently, he has been active in the development smart sensors for system health management for NASA's rocket propulsion test platforms at John C. Stennis Space Center.

Co-Principal Investigator: Professor Robi Polikar (Ph.D. 2000, Iowa State University) has a unique background in classical pattern recognition techniques combined with novel methods for biomedical signal analysis. In particular he has developed novel evolutionary learning algorithms which are uniquely suited to the management of large, complex and evolving data sets, characteristic of pipeline inspection.

Collaborator (Subcontractor): Crane Company (NYSE: CR) is a diversified manufacturer of engineered industrial products with its headquarters in Stamford, CT. Advanced Integrated Systems Division (AISD) is part of the Aerospace & Electronics segment of Crane. AISD has core competencies in wireless communications, wireless networking and product development.

b. Demonstrated corporate experience of the applicant and participating organizations in managing similar projects.

A leading public institution in Southern New Jersey, Rowan University, formerly Glassboro State College (founded 1923) offers programs from the baccalaureate through the doctorate. The College of Engineering was created in 1995 by a transformational gift of $100 million from industrialist Henry M. Rowan. This project will be supported by the Nondestructive Evaluation and Imaging Laboratory, housed in the Department of Electrical & Computer Engineering.

The NDE laboratory supports research in magnetic, ultrasonic, acoustic, optical and X-ray CT imaging, design and development of artificial neural networks and virtual reality (VR). The lab has pioneered the application of a variety of imaging techniques for non-invasive materials assessment and shape characterization. Faculty, students and industrial collaborators have addressed a variety of 2-D and 3-D shape characterization problems such as –

- Stress-corrosion-cracking defects in gas transmission pipelines using acoustic imaging;
- Mechanical damage defects in gas transmission pipelines using thermal imaging
- Corrosion damage defects in gas transmission pipelines using magnetic and ultrasonic imaging;
- Crown-corrosion damage defects in wastewater concrete pipelines using ultrasonic imaging;
- Stress-corrosion-cracks in nuclear power plant tubing using photothermal imaging
- Three-dimensional shape characterization of geomaterial aggregates;
- Identification and segmentation of radiodense tissue in digitized mammogram X-rays;
- Virtual reality displays of underground gas transmission pipeline inspection;
- Virtual prototyping of DD(X) Destroyer battleship engine rooms.

To date, the laboratory has secured over $2M in research funding from sponsors such as National Science Foundation, US Department of Energy, National Institutes of Health, US Navy, American Cancer Society, ExxonMobil, Thomson Consumer Electronics, Water Environment Research Foundation, etc. A multidisciplinary team of faculty and students from Electrical & Computer Engineering, Civil & Environmental Engineering and Mechanical Engineering participate in lab projects. There is also strong research collaboration local industry and with Fox Chase Cancer Center in Philadelphia, PA.

Crane Company (NYSE: CR), founded in 1855, has about 10,500 employees and supports products in 30 countries in highly-focused niche markets. Advanced Integrated Systems Division (AISD) was part of the Crane acquisition of Signal Technology in 2003. AISD has recently focused on the emerging market for wireless sensor systems. They currently employ almost 40 engineers and are sustaining a rapid growth rate. AISD is committed to working with academia, military, homeland security, and other agencies to understand their needs and work diligently to find solutions. AISD has recently partnered with sister division Crane Valve Services to develop and market a wireless remote monitoring solution used in upstream and downstream oil & gas applications. The solution provides online, condition-monitoring solution for shutdown valves.

c. Clarity, logic and likely effectiveness of project organization including subcontractors to successfully complete the project. The adequacy and availability of the personnel, facilities and equipment to perform project tasks.

Project task responsibilities are shared between Rowan University (prime) and Crane Aerospace & Electronics (subcontractor). RTD Quality Services will lead efforts to provide real pipeline inspection data. The current hardware assets at Rowan University devoted to this project include ultrasonic, magnetic, acoustic, thermal, optical and X-ray CT imaging stations; optical tables and precision x-y-z scanning systems, a medical-grade X-ray digitizer, a FakeSpace semi-immersive Virtual Reality system, PC and Linux workstations. Current software assets include MATLAB and associated image processing/signal processing/neural network toolboxes, Visual C++, VGeo, OpenInventor, Deep Exploration, 3DStudioMax, etc.