<u>Quarterly Progress Report</u>:
Project Number and Title: 1.6 Progressive fault identification and prognosis of railway tracks based on intelligent inference
Research Area: #1 Transportation infrastructure monitoring and assessment for enhanced life
PI: Jiong Tang, Department of Mechanical Engineering, University of Connecticut
Co-PI(s): N/A
Reporting Period: 1/1/2020 – 03/31/2020
Submission Date: 03/31/2020

<u>Overview:</u> (Please answer each question individually)

The goal of this project is to develop highly accurate and robust fault identification and prognosis methods specifically tailored for railway track systems. In this project period, we further continue our research on formulating physics-informed inverse identification algorithms. Here we focus on a multi-objective optimization technique to tackle challenge in inverse identification. With damage locations and severities as unknown variables, one of the objective functions is the difference between impedance-based model prediction in the parametric space and the actual measurements. Considering that damage occurrence generally affects only a small number of elements, we choose the sparsity of the unknown variables as another objective function, deliberately, the l0 norm. Subsequently, a multi-objective Dividing RECTangles (DIRECT) algorithm is developed to facilitate the inverse analysis. Specifically in this project period, we carry out comprehensive case studies to validate the algorithm.

Provide context as to how these activities are helping achieve the overarching goal(s) of the project…

In the previous phases of the project (10/31/2018 – 12/31/2019), we perform preliminary investigation on sensing mechanism development and inverse identification algorithms. Through circuitry integration and tunable resonance, we can greatly enhance the impedance/admittance measurement quality and also enrich the measurement information. Subsequently, we have formulated and executed fault identification built upon Bayesian inference. Simulation data were then used to practice the identification of fault location and severity. The outcome provides a preliminary demonstration of the feasibility of Bayesian inference for fault identification with pre-screening. The activities carried out in this project period have demonstrated that pre-screening can indeed be realized with multiple-damage scenario.

Describe any accomplishments achieved under the project goals…

As explained in the preceding quarterly report, we cast the inverse identification problem into an optimization framework. Let $\Delta\mathbf{Y}$ be the measured admittance change. The prediction of admittance change in the parametric space is denoted as $\Delta\hat{\mathbf{Y}} = \mathbf{S}\hat{\boldsymbol{\alpha}}$. Certainly, we need to minimize the difference between these two. It is worth noting that a true damage scenario in practical situation usually affect only a small number of segments. In other words, the damage index vector $\boldsymbol{\alpha}$ is sparse by nature. Here we introduce the sparse regularization by enforcing a sparse constraint on $\hat{\boldsymbol{\alpha}}$. In this research, we formulate a multi-objective optimization,

$$\text{Find: } \hat{\boldsymbol{\alpha}} = \{\hat{\alpha}_1, \hat{\alpha}_2, ..., \hat{\alpha}_n\}, \quad \alpha^l \le \hat{\alpha}_j \le \alpha^u, \quad j = 1, 2, ..., n$$
$$\text{Minimize: } f_1 = \|\mathbf{S}\hat{\boldsymbol{\alpha}} - \Delta\mathbf{Y}\|_2 \text{ and } f_2 = \|\hat{\boldsymbol{\alpha}}\|_0 \tag{1}$$

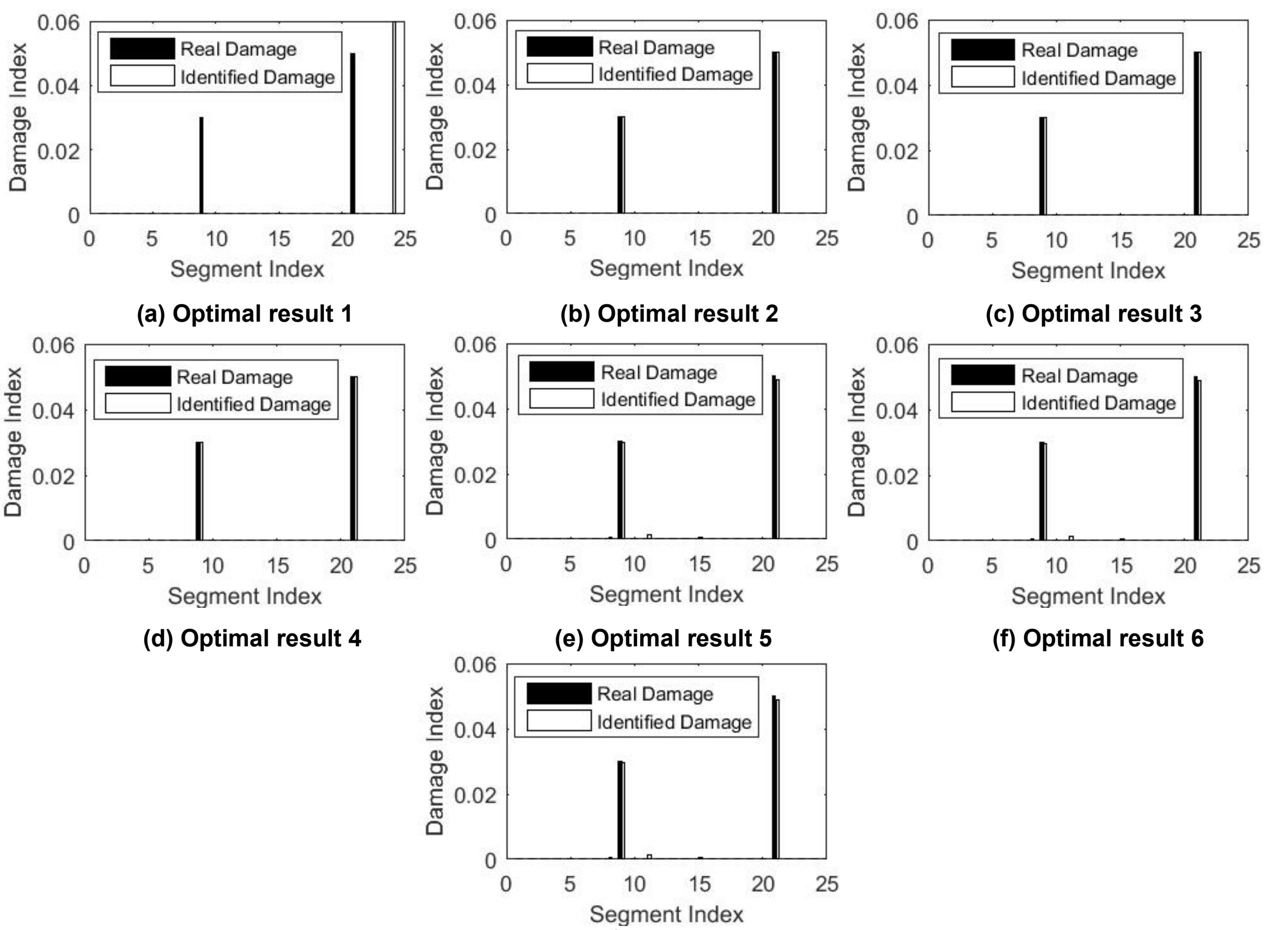
where α^l and α^u are the lower bound and upper bound of the damage index. A fundamental advantage of this multi-objective optimization formulation is that it naturally yields a set of optimal solutions explicitly exhibiting the tradeoff between objectives, i.e., the Pareto front/surface. This fits exactly the under-determined nature of the damage identification problem, and provides identification results that can be used for further inspection and prognosis.

We carry out comprehensive numerical case studies. We consider an aluminum cantilever plate. The finite element model of the plate has 11,250 ($375 \times 15 \times 2$) 20-node hexahedron elements. It is further divided into 25 segments for damage identification indicating 25 possible damage locations. The segments are evenly divided along the length direction of the plate. In damage detection using admittance measurements, the admittance changes due to damage occurrence are most evident around the resonant peaks. Without loss of generality, we acquire the admittance change information around the plate's 14^{th} (1893.58 Hz) and 21^{st} (3704.05 Hz) natural frequencies. By keeping the linearly dependent rows of the sensitive matrix, a total of 21 useful measurements around the two natural frequencies (from 1891.69 Hz to 1895.47 Hz and from 3700.35 Hz to 3707.75Hz) are employed in the inverse analysis.

We perform test with two randomly selected damage locations on the 9th and 21st segment with severities $\alpha_9 = 0.03$ (3% stiffness loss) and $\alpha_{21} = 0.05$ (5% stiffness loss) respectively. As shown in Table 1, multiple optimal solutions are produced by the sparse multi-objective DIRECT optimization. The solutions obtained exemplify the tradeoff between residue and the number of damage locations. In other words, the solution with smaller residue may have more predicted damaged segments. As shown in Figures 1(b)-(g), optimal results 2 to 7 are relatively similar to each other in terms of identified results. In genetic algorithm description, they are considered to belong to the same niche. Consider optimal results 2 (Figure 1(b)) and 7 (Figure 1(g)) as example. The latter has two major damages (similar to optimal result 2) and six more negligible damages that reflect the error introduced by linear approximation and analytical modeling. Since the number of damage is unknown in practice, we could consider the niches of optimal result 1 and 2 as possible candidates. However, as illustrated in Figure 11, optimal result 2 matches the input data better than optimal result 1 in terms of residue value. Thus, the niche of optimal result 2 is preferable, which indeed agrees with the true damage scenario.

Table 1. Optimal results: numerical test case 1.

Optimal Results	Residue (f_1 in Equation (12))	# of Damage (f_2 in Equation (12))
1	1.8223e-07	1
2	1.1771e-10	2
3	1.1770e-10	3
4	1.1763e-10	4
5	1.1704e-10	5
6	1.1698e-10	6
7	1.1698e-10	7



(a) Optimal result 1 **(b) Optimal result 2** **(c) Optimal result 3**

(d) Optimal result 4 **(e) Optimal result 5** **(f) Optimal result 6**

(g) Optimal result 7

Figure 1. Test case: real damage scenario compared with predicted damage scenarios.

Complete the following tables to document the work toward each task and budget (add rows/remove rows as needed, make sure you complete the Overall Project progress row and include all tasks even if they have ended or have not been started)…

Table 1: Task Progress

Task Number	Start Date	End Date	% Complete
Task 1:	09/2018	03/2020	100%
Task 2:	04/2020	03/2021	30%
Task 3:	03/2021	03/2022	10%
Task 4:	04/2022	09/2023	30%

Table 2: Budget Progress

Project Budget	Spend – Project to Date	% Project to Date*
$254,000	$68,458.32	27% (3/31/2020)

Include the date the budget is current to.

Describe any opportunities for training/professional development that have been provided…

This project has involved one M.S. student, Yixin Yao, who carries out the numerical and experimental investigations, and one Ph.D. student, Yang Zhang, who focuses on improving the fault identification and prognosis algorithms. Starting in fall 2019, 4 undergraduate senior students from UConn Management and Engineering of Manufacturing Program, Alexander Biron, Kelly Quinn, Jason Trieu, and Meghan Palumbo, have been developing an experimental testbed which is partially supported by this project. These involvements provide opportunity for training. The project progress is being communicated with industry collaborator, Sperry Rail Service, which provides another opportunity for training of state-of-the-art knowledge of active materials and advanced signal processing techniques for working professionals.

Describe any activities involving the dissemination of research results (be sure to include outputs, outcomes, and the ways in which the outcomes/outputs have had an impact during the reporting period. Please use the tables below for any Publications and Presentations in addition to the description of any other technology transfer efforts that took place during the reporting period.)… Use the tables below to complete information about conferences, workshops, publications, etc ***. List all other outputs, outcomes, and impacts after the tables*** *(i.e. patent applications, technologies, techniques, licenses issued, and/or website addresses used to disseminate research findings).*

Table 3: Presentations at Conferences, Workshops, Seminars, and Other Events

Title	Event	Type	Location	Date(s)
N/A				

Table 4: Publications and Submitted Papers and Reports

Type	Title	Citation	Date	Status
N/A				

<u>Participants and Collaborators:</u>

Use the table below to list all individuals who have worked on the project.

Table 5: Active Principal Investigators, faculty, administrators, and Management Team Members

Individual Name	Email Address	Department	Role in Research
Jiong Tang	jiong.tang@uconn.edu	Mechanical Engineering	PI

Use the table below to list all students who have participated in the project during the reporting. (This includes all paid, unpaid, intern, independent study, or any other student that participated in this project.)

Table 6: Student Participants during the reporting period				
Student Name	**Email Address**	**Class**	**Major**	**Role in research**
Yixin Yao		M.S.	Mechanical Engineering	Carry out simulation and experiment
Yang Zhang		Ph.D.	Mechanical Engineering	Carry out inverse identification
Alexander Biron		Senior	MEM	Assist testbed setup
Kelly Quinn		Senior	MEM	Assist testbed setup
Jason Trieu		Senior	MEM	Assist testbed setup
Meghan Palumbo		Senior	MEM	Assist testbed setup

Use the table below to list any students who worked on this project and graduated during this reporting period.

Table 7: Student Graduates			
Student Name	**Role in Research**	**Degree**	**Graduation Date**
N/A			

Use the table below to list organizations have been involved as partners on this project and their contribution to the project.

Table 8: Research Project Collaborators during the reporting period						
Organization	**Location**	**Contribution to the Project**				
		Financial Support	**In-Kind Support**	**Facilities**	**Collaborative Research**	**Personnel Exchanges**
Sperry Rail Service	Shelton, CT		X	X		
Connecticut Manufacturing Simulation Center	Storrs, CT		X	X		

List all other outputs, outcomes, and impacts here (i.e. patent applications, technologies, techniques, licenses issued, and/or website addresses used to disseminate research findings). Please be sure to provide detailed information about each item as with the tables above.
N/A

Have other collaborators or contacts been involved? If so, who and how? (This would include collaborations with others within the lead or partner universities; especially interdepartmental or interdisciplinary collaborations.)

Table 9: Other Collaborators			
Collaborator Name and Title	**Contact Information**	**Organization and Department**	**Contribution to Research**
N/A			

Who is the Technical Champion for this project?
Name: Jan Kocur

Title: Director of Engineering
Organization: Sperry Rail Service
Location (City & State): Danbury, CT
Email Address: jkocur@sperryrail.com

Changes:

Discuss any actual or anticipated problems or delays and actions or plans to resolve them…
N/A
Discuss any changes in approach and the reasons for the change…
N/A

Planned Activities:

The next phase of the research will focus on completion of fault diagnosis.