A Software Tool for Optimal 2D Placement of Sensors, Including Human Inspection, for Locally Degraded Structures (SHM2Opt)

Amin Aria[a*], Shapour Azarm[b], and Mohammad Modarres[a]
[a] Center for Risk and Reliability, University of Maryland, College Park, MD, USA
[b] Department of Mechanical Engineering, University of Maryland, College Park, MD, USA

Abstract: Structures such as pipelines fail due to the underlying failure mechanisms associated with localized degradations. Such degradations are difficult to monitor and can lead to structural failures as well as human and economic risks. To prevent such failures, several Health Monitoring (HM) schemes are reported in the literature where sensor network design and Human Inspection (HI) planning are among the most popular ones. However, most of the extant approaches, and corresponding HM design tools, consider these schemes separately while either reliability or cost is overlooked in the design of final HM layout. In addition, simplifying assumptions, such as linear geometry of the final layout, are used to ease corresponding computations. A software tool (SHM2Opt) for optimal 2D placement of sensors, including HI, is introduced in this paper. SHM2Opt is developed based on a cost-effective and reliable HM approach developed by the authors. Knowing HM data history of a structure and using the developed approach, the final output of SHM2Opt would be a 2D layout of the structure consisting location of sensors of different types and an appropriate HI scheme. One notional example is also solved to show capabilities and applicability of the presented software tool.

Keywords: Degraded Structure, Human Inspection, Health Monitoring, Placement, Sensor

1. INTRODUCTION

Structures such as pipelines, bridges, and railways are subject to localized degradations such as corrosion. These degradation processes are slow and usually lead to localized damages. Also, the growth of such damages is slow in the early life stage of structures. However, such degradation processes and resulting damages can be overlooked and lead to catastrophic failures in older structures.

Sensor network design and HI planning are among the popular schemes in the Structural Health Monitoring (SHM) literature. However, HM layouts (placement of sensors and human inspection) obtained as a result of existing approaches are most often not optimal. First, SHM schemes, e.g. sensor network design and HI, are mostly considered separately in the extant SHM optimization models [1, 2]. In addition, multiple simplifying assumptions are considered in the reported approaches. For instance, consideration of only a single sensor type and linear placement of sensors in a network are among the popular assumptions used for sensor network design [3, 4]. On the other hand, the literature on HI planning mostly neglects the validity and level of inspector skill and attributes of the NDT tools [2, 5]. Furthermore, either cost or reliability is considered as the objective function of SHM optimization problems in the literature [6]. This paper presents a novel software tool to identify an HM layout that optimizes cost and reliability of damage detection and sizing concurrently.

To implement the SHM approach developed by the authors [7], where sensor network design and HI are considered simultaneously under few simplifying assumptions, a software tool is developed and presented in this paper. This tool can be used to find the optimal layout corresponding to a particular structure subjected to localized degradation, where there is prior knowledge on the initial state of the structure. The software tool consists of several interacting modules, coded in different languages. The final output of this software tool is an optimal 2D HM layout.

[*] aaria@umd.edu

The remainder of this paper is organized as follows. First, an overview of the software tool, in addition to detailed explanation of its modules, are presented in Section 2. Next, in Section 3, one notional example is solved to demonstrate capabilities of the tool and applicability of the underlying approach. Finally, the paper is concluded with a summary in Section 4.

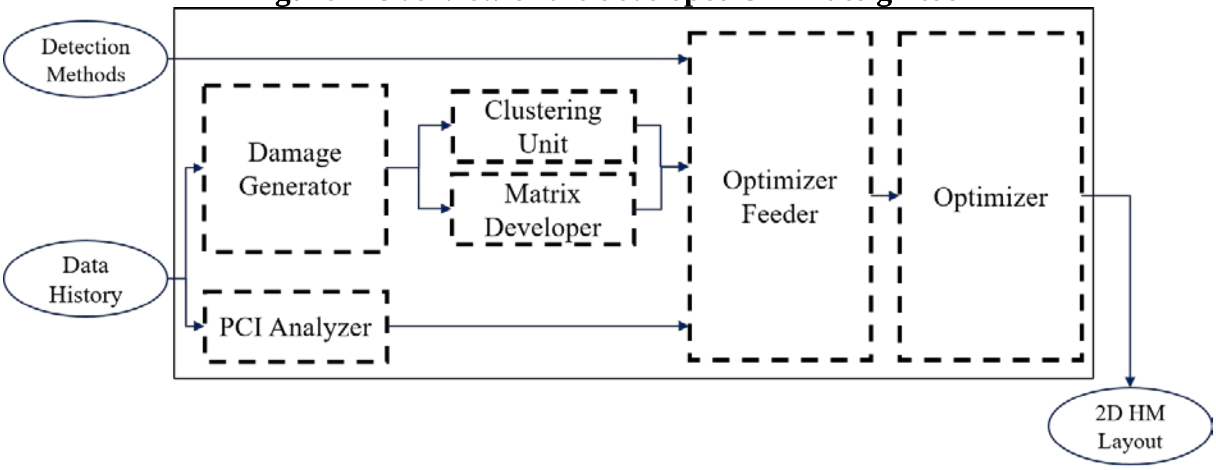
2. SHM2Opt OVERVIEW and MODULES EXPLANATION

An overview of the SHM2Opt is schematically depicted in Figure 1. The input of the developed tool is available detection methods (e.g. acoustic emission sensor network and HI with ultrasonic NDT tool) and data history on the structure under study. The output of the tool is a 2D HM layout, which includes placement of sensors as well as HI on the exterior surface of the structure. The HI modeling used is discussed in [7]. It considers HI as sensors with high coverage capability and low data acquisition frequency.

Six main modules shape the SHM2Opt. The first module is the “Damage Generation” module that takes structural monitoring data history as the input and produces a random realization of damages produced through Monte-Carlo simulation on a 2D surface representation of the structure as an output. This output is fed into the ‘Matrix Developer’ and ‘Clustering Unit’ Modules. Matrix Developer module produces matrices associated with calculations regarding detection of damages of the input realization. Clustering Unit module cluster the damages of the input realization to mitigate optimization computation burden. In the meanwhile, Partial Coverage Inspection (PCI) analysis [8] is carried out in the “PCI Analyzer” module on the structure monitoring data history.

In the next step, matrices, clusters, and available detection methods as well as PCI results, are fed into “Optimizer Feeder” module where constraints and bounds of the optimization problem are defined. At last, constraints and bounds are exported to the “Optimizer” module to find the optimal 2D HM layout with minimized metric of utility (including cost) and maximized metric of detection.

Figure 1-Overview of the developed SHM design tool



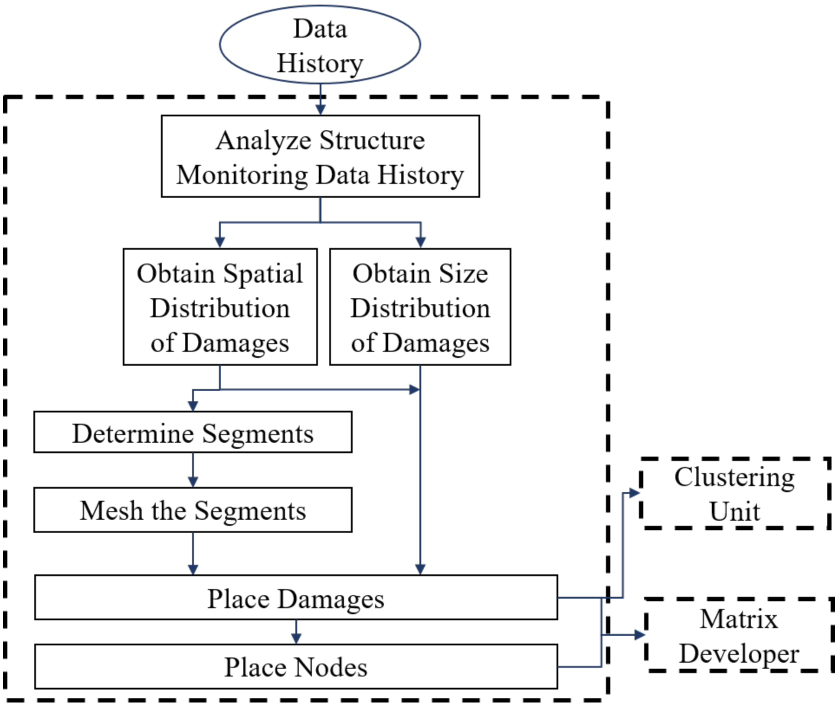
Detailed explanation of each of the modules are followed.

2.1 Damage Generator Module

At the very first point, a random realization of the structure under investigation (e.g., a segment of a pipeline structure) should be generated. To do so, Damage Generator module, illustrated in Figure 2, is used. This module is fully coded in R®. Structure monitoring data history is analyzed to obtain probabilistic spatial distribution of damages over the surface of the structure. Additionally, probabilistic size distribution of damages is also attained considering data history analysis. To find the appropriate characteristics of damages and their distributions, this part is mostly consisted of regression analysis and model fitting.

Next, probabilistic spatial distribution of damages is used to determine structure segments having uniform longitudinal intensity of damages. Then, a segment under study will be meshed in a way that probability of having more than one damage in each cell is negligible [7]. Following that, using a Monte Carlo sampling method, damages with different sizes are placed at meshes (i.e., generating a realization of a hypothetical structure with specific damages). In the next step, nodes nodes, as the potential location of sensors or HI, are placed assuming there are equal number of damages and nodes in each realization. It is possible that no detection method is assigned to one node. Damages and nodes configuration, as the output of Damage Generator module, feed their values into the Matrix Developer and Clustering Unit modules.

Figure 2 - Damage Generator module of the developed tool

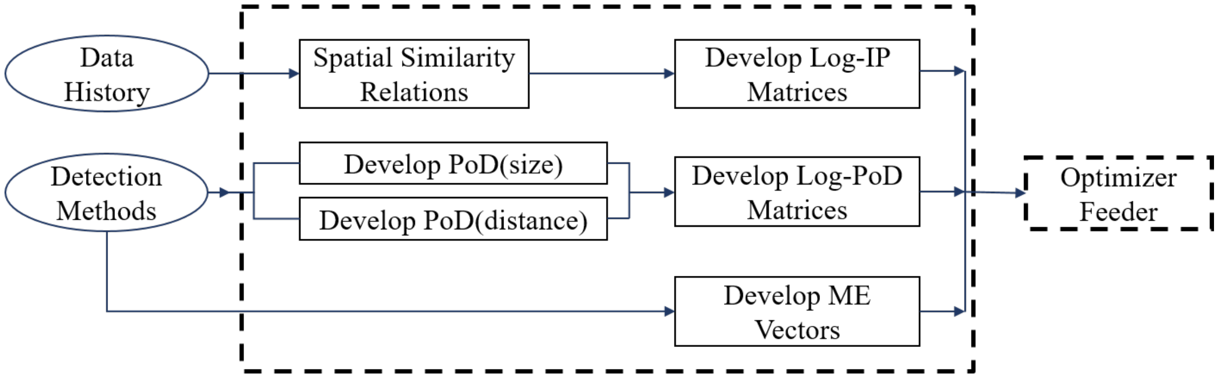


2.2 Matrix Developer Module

Three detection metrics, namely Probability of Detection (PoD), Inference Probability (IP) and probabilistic Measurement Error (ME) are concurrently considered in the approach developed by authors [7]. The PoD is a function of damage size and distance from the means of detection (i.e., a sensor or HI). The IP is the probability of true prediction of state of the structure (i.e., presence of a damage of a particular type and size) considering the HM data at another location [7]. The probabilistic ME is defined as the reported size value of a damage at a certain distance from a particular detection tool differs lays in the acceptable size interval considering true damage size [7].

To make it possible to use these metrics in the context of optimization, matrices corresponding to logarithm of PoD and IP, as well as probabilistic ME, are developed in R® considering damages and nodes configuration over the surface of the structure. Log-IP matrices are developed considering spatial similarity relations (matrices) of the points over the structure surface. These relations are deduced from data history analysis. On the other hand, log-PoD matrix, for each detection method, is obtained through multiplication of marginal PoD as a function of size and distance (The independence of PoD(size) and PoD(distance) is assumed here). In addition, ME vector is developed for each of detection methods using the proposed damage classification method presented in [7]. The entire Matrix Development module is developed in R®. Lastly, log-IP and log-PoD matrices, as well as ME vectors input their results into the Optimizer Feeder module.

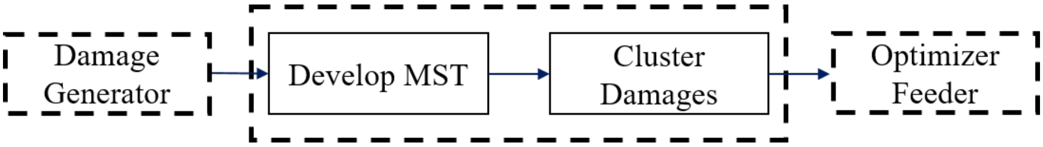
Figure 3-Matrix Developer Module of the developed tool



2.3 Clustering Unit Module

To reduce feasible regions without concern over sub-optimality[7], damages of each realization are clustered using the Kruskal Minimal Spanning Tree (MST) [9] approach and constrained K-means clustering [10] method. Details of the underlying approach are discussed in [7]. The Clustering Unit Module is developed in Python® and the obtained clusters feed into the Optimizer Feeder.

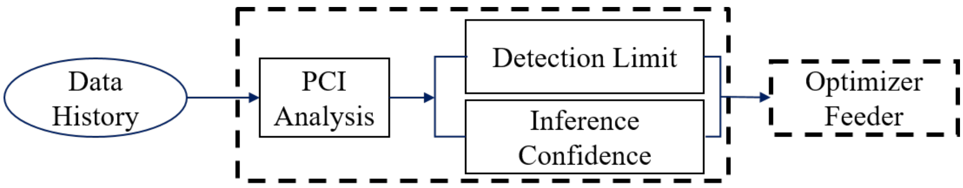
Figure 4-Clustering Unit Module of the developed tool



2.4 PCI Analyzer Module

PCI is a statistical method that determines required sample size to have the worst-case data points (here damages) with a particular confidence level [8]. In other words, PCI determines required coverage (detection limit) over the surface under investigation to guarantee having the worst-case damage (of the largest size) with P% confidence (inference confidence) in the sample. A module that carries out this process, considering the detailed explanation is provided in [8], can be easily developed. However, it is assumed that detection limit and inference confidence are known a priori for the structure under study and are used in the Optimizer Feeder module.

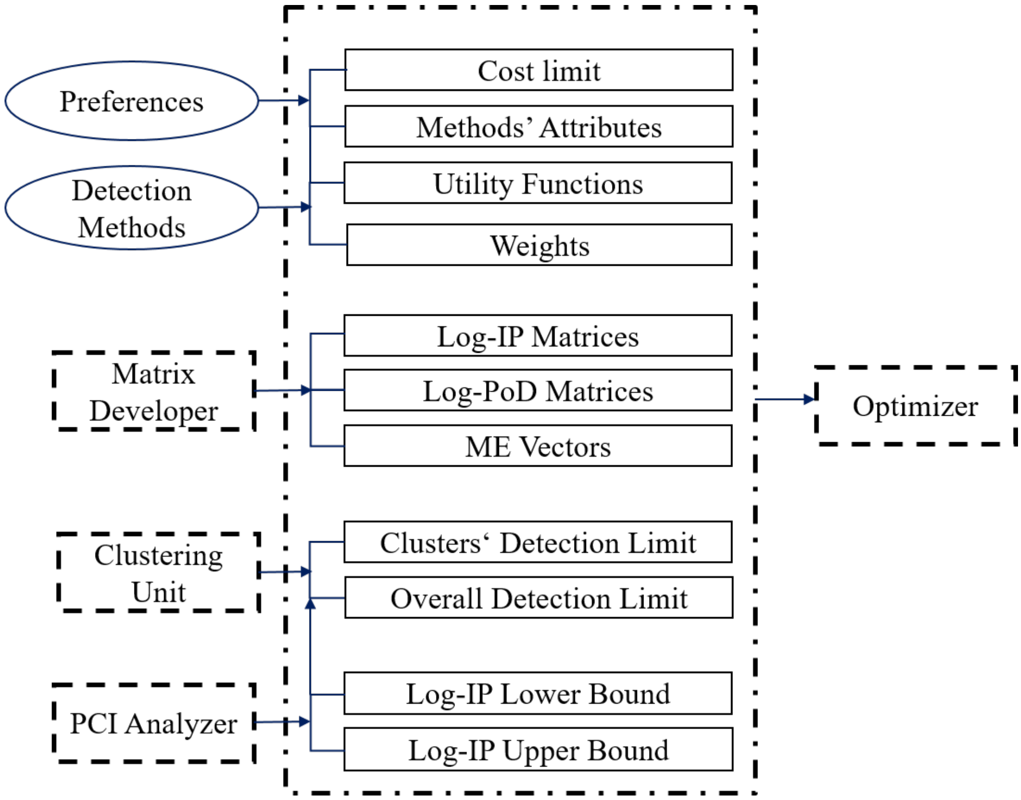
Figure 5-Proposed PCI Analyzer Module



2.5 Optimizer Feeder Module

To define optimization constraints and corresponding bounds, Optimizer Feeder module (Figure 6) is developed. This module is a Microsoft Excel® file that contains all the input material of the Optimizer Module. Total cost limit is determined considering decision makers' preferences. In the meanwhile, attributes to be considered (e.g. detection method cost, data acuqision frequency, and precision of detection methods (ME)) are determined. Normalized utility of each of the attributes is determined for each of detection methods considering utility functions proposed by the experts. Finally, weighted utility of attributes will be summed to shape the utility of each of detection methods. Note that total utility (sum of utilities of all detection methods used) is one of the objective functions of the Optimizer module.

Figure 6-Optimizer Feeder Module of the developed tool



Log-IP and log-PoD matrices are fed into Optimizer Feeder module to be used in calculation of Logarithm of Probability of Not Detection (LPoND) of the damages in each structural damage realization under consideration. Minimizing average LPoND (that is equivalent to geometrical average of PoND of all the damages) is another objective function of the Optimizer module. ME vectors will be used to calculate precision of each of detection methods, if assigned to any of the nodes.

In the meanwhile, clusters and results of PCI analysis are fed into the Optimizer Feeder module to determine cluster's detection lower bound using Eq. (1) :

$$LB_{C_i} = \left\lfloor \frac{N_i \times OB}{N} \right\rfloor \qquad (1)$$

where LB_{C_i} is the detection lower bound of cluster i, N_i is number of damages in cluster i, N is the total number of damages in the realization, and OB is the overall detection lower bound determined following the PCI analysis. Results of the PCI analysis is used to determine upper and lower bounds of log-IP of each of the damages, as well.

2.6 Optimizer Module

The HM design optimization problem at hand is formulated in GAMS® using BARON Mixed Integer Non-Linear Programming (MINLP) solver [11]. The input is read from the Optimizer Feeder MS Excel® file. The problem is formulated as an all-in-one single objective, where the objective function is the weighted sum of total utility and average LPOND [7]. The final result is a configuration of sensors and HI, including their placement, with maximum total utility and minimum average LPoND.

The final result for the decision maker, can be an aggregate 2D layout obtained through combination of the HM layouts corresponding to different realizations of the structure using Wilks method [7,12].

An example follows next to demonstrate capabilities and applicability of the approach and the software tool SHM2Opt.

3. Notional Example

A notional example, using synthetic internal pitting corrosion data on a pipeline structure, is solved using the SHM2Opt. A hypothetical 50 meter long, 0.5 meter radius pipeline segment with uniform longitudinal distribution of pits is assumed assuming acoustic emission sensors and HI using an ultrasonic NDT tool as two available detection methods with particular attributes.

Following analysis of pipeline monitoring data history, it is assumed that longitudinal intensity of pits over the pipeline segment is 0.24 pits per meter over the length of the pipeline. Also, the distribution provided in [13] is used for the size distribution of the pits depth (pit length is neglected). Four damage classes are defined [7], as presented in Table 1. Note that in the particular realization under study, no damages of classes three of four are generated and all damages belong to classes one and two.

To account for circumferential variability of location of damages, it is assumed that damages distribution follow Eq. (2) :

$$D_c \sim N(0, \frac{\pi R}{3}) \tag{2}$$

where D_c is the circumferential location of a damage at the 2D roll-out of the pipeline and zero is at the bottom-line of the pipeline (refer to Figure 7 for better illustration). As such, higher density pits are located at the bottom of the pipeline.

For longitudinal location of damages, Homogenous Poisson Process (HPP) is assumed over mesh sizes with 0.5 meters wide. Placement of damages in the realization under study is presented in Table 1 where x and y denote longitudinal and circumferential location of damage at rectangular roll-out of the pipeline segment under study. The origin of the coordinates is the left-most point of the segment bottom-line.

Table 1- Location of damages in pipeline realization

Damage#	x(m)	y(m)	Damage Class [interval (mm)]
1	2.25	0.25	2 [0.19 0.32]
2	3.26	0.67	1 [0 0.19]
3	3.77	2.74	1 [0 0.19]
4	4.78	0.31	1 [0 0.19]
5	13.87	0.16	2 [0.19 0.32]
6	29.53	0.28	2 [0.19 0.32]
7	31.55	0.23	1 [0 0.19]
8	37.10	2.55	2 [0.19 0.32]
9	38.11	0.39	1 [0 0.19]
10	41.14	0.37	2 [0.19 0.32]

Nodes, as the potential location of sensors or HI, are generated with their longitudinal exactly same as the corresponding damage [7] and circumferential component obtained through adding a random value in the interval [-0.5 0.5] to that of the corresponding damage. It is assumed that coverage radius of acoustic emission sensors is 0.4 meters and, thus, the random interval for circumferential placement of nodes is such chosen. For more information, refer to [7].

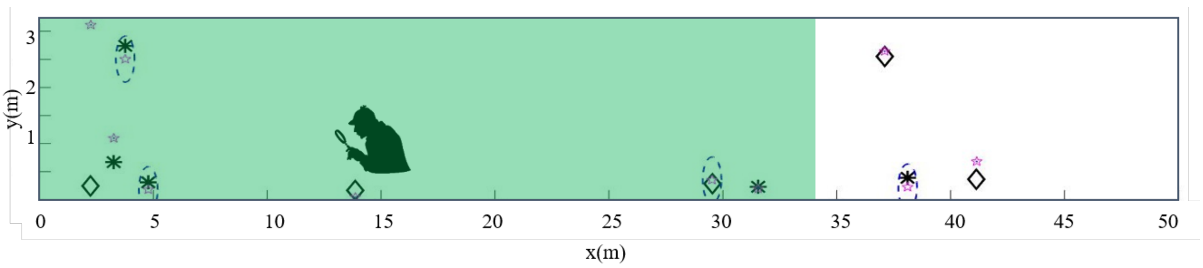
ME vectors are obtained using ME models provided in [14] and [15] for acoustic emission sensors and ultrasonic NDT tool, respectively. In the ME part of Matrix Developer module, data points are sampled from truncated distributions corresponding to the four classes of pit size distribution and simulated reported values are obtained considering underlying ME models. At last, the probability that reported values lay in the original size interval of the damage is calculated as the probabilistic ME for each of pits (with known size) that might be detected by each of available detection methods.

On the other hand, PoD(size) and PoD(distance) is calculated for each of detection methods considering relations provided in [2,15,16]. In addition, assuming distance as the only similarity metric for development of IP values, log-IP matrices are developed for all combinations of damage classes and available detection methods.

It is also assumed that following PCI analysis, the overall detection limit is found to be 50%. In addition, three clusters of damages are defined considering length of MST edges. In the meanwhile, detection lower bound is defined for each cluster considering the overall detection limit. Lastly, for a set of subjective weights and utility functions, proposed by authors, the final 2D HM layout is obtained.

The optimal 2D HM layout, with minimum average LPoND and maximum total utility, corresponding to the realization under study, is illustrated in Figure 7 where asterisks and diamonds denote damages that belong to classes one and two. Stars represent nodes and dashed circles represent coverage boundary of the acoustic emission sensor. In addition, shaded area represents inspection area.

Figure 7- 2D HM layout corresponding to the realization under study



4. CONCLUSION

A software tool, SHM2Opt, based on a reliable and cost-effective approach for optimal placement of sensors, including HI, is presented. SHM2Opt consists of five pre-processing modules, which are coded in R® and Python®, and one optimization module that is coded in GAMS®. The final output of the tool is a 2D layout including inspection area as well as placement of sensors with minimized metric of cost and maximized metric of detection. An example is provided that demonstrates application and practicality of SHM2Opt.

Acknowledgements

This work was carried out as a part of the Pipeline System Integrity Management Project, which was supported by the Petroleum Institute, Khalifa University of Science and Technology, Abu Dhabi, UAE. This support is gratefully acknowledged.

References

[1] H.A. Kishawy and H.A. Gabbar. “Review of pipeline integrity management practices”, International Journal of Pressure Vessels and Piping, 87(7), pp.373-380 (2010).
[2] S. Zhang and W. Zhou, “Cost-based optimal maintenance decisions for corroding natural gas pipelines based on stochastic degradation models”, Engineering Structures, 74, pp.74-85 (2014).
[3] J.P. Watson, H.J. Greenberg, and W.E. Hart, “A multiple-objective analysis of sensor placement optimization in water networks”, Critical Transitions in Water and Environmental Resources Management, pp. 1-10 (2004).
[4] C. Zhu, C. Zheng, L. Shu, and G. Han,” A survey on coverage and connectivity issues in wireless sensor networks”, J. of Network and Computer Applications, 35(2), pp.619-632(2012).
[5] K.E. Perumal, “Corrosion risk analysis, risk based inspection and a case study concerning a condensate pipeline”, Procedia Engineering, 86, pp.597-605 (2014).
[6] M. Younis and K. Akkaya, “Strategies and techniques for node placement in wireless sensor networks: A survey”, Ad Hoc Networks, 6(4), pp.621-655 (2008).
[7] A. Aria, S. Azarm, M. Modarres, “Optimizing Sensor and Human Inspection Network Layout for Time-invariant Health Monitoring of Localized Corrosion in Pipelines”, International Journal of Reliability and Safety”, submitted to be published
[8] D. Benstock and F. Cegla, “Sample selection for extreme value analysis of inspection data collected from corroded surfaces”, Corrosion Science, 103, pp.206-214 (2016).
[9] J.B. Kruskal, “On the shortest spanning subtree of a graph and the traveling salesman problem”, Proceedings of the American Mathematical society, 7(1), pp.48-50 (1956).
[10] K. Wagstaff, C. Cardie, S. Rogers, and S. Schrödl, “Constrained k-means clustering with background knowledge”, ICML,Vol. 1, pp. 577-584, (2001).
[11] M. Tawarmalani and N.V. Sahinidis, “A polyhedral branch-and-cut approach to global optimization”, Mathematical Programming, 103(2), pp.225-249 (2005).
[12] S.S. Wilks, “Determination of sample sizes for setting tolerance limits”, The Annals of Mathematical Statistics, 12(1), pp.91-96 (1941).
[13] C.I. Ossai, B. Boswell, and I.J. Davies, “Predictive modelling of internal pitting corrosion of aged non-piggable pipelines”, Journal of The Electrochemical Society, 162(6), pp.C251-C259 (2015).
[14] M. Rabiei and M. Modarres, “Quantitative methods for structural health management using in situ acoustic emission monitoring”, International J. of Fatigue, 49, pp.81-89 (2013).
[15] K. Chatterjee and M. Modarres, “A probabilistic approach for estimating defect size and density considering detection uncertainties and measurement errors”. Proc. of the Institution of Mechanical Engineers, Part O: J. of Risk and Reliability, 227(1), pp.28-40 (2013).
[16] A. Pollock, “Probability of detection for acoustic emission” Journal of Acoustic Emission, 25, pp.231-237 (2007).