2020 INFORMS QSR Student Interaction and Poster Competition

4:30 PM - 5:45 PM Monday, November 9, 2020
Virtual Room 44

Student Introduction and Interaction Session
& Best Student Poster Competition
Quality, Statistics and Reliability (QSR) Section

The session is designed for QSR student members to build their professional network, show up their talents, and learn from invited guests. In this session, each student will deliver an elevator speech about his/her research interests and accomplishments. Senior QSR members, junior faculty members are invited to interact with all attendees. A parallel Best Student Poster Competition session is pre-recorded. A winner will be selected by a panel of judges, announced at the QSR business meeting, and awarded a certificate. The Student Introduction and Interaction session and Best Student Poster Competition are sponsored by the QSR Section of the INFORMS.

PROGRAM AT GLANCE:

Live session: Student Introduction and Interaction
4:30 PM – 5:45PM (EDT), November 09, 2020
Virtual Room 44

- 4:30 – 4:45 pm: Panelists' Introduction
- 4:45 – 5:20 pm: Student Elevator Speech, 2 min / each student
- 5:20 – 5:45 pm: Mini-panel, Q&As, and open interactions with the panelists

Pre-recorded session: Best Student Poster Competition

Ahmed Aziz Ezzat, Ph.D.
Assistant Professor
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INVITED GUESTS

DR. SUSAN ALBIN

PROFESSOR
DEPARTMENT OF INDUSTRIAL AND SYSTEMS ENGINEERING
RUTGERS UNIVERSITY

BIO

Dr. Susan Albin is a Professor in the Department of Industrial Engineering at Rutgers University. Her research fields are quality engineering, statistical process control, data analytics, and stochastic modeling. Her work has been applied in areas including semiconductor manufacturing, plastics recycling, food processing, and medical devices. Dr. Albin's work has been supported by NSF, FAA, DOD, and industrial partners. Dr. Albin received her doctorate from Columbia University. She has served as President of INFORMS, editor-in-chief of IIE Transactions, and was the founding advisory board chair for QSR. On her sabbatical she helped establish a Quality Engineering program at Penninsula Technicon in South Africa. Her current focus is on active learning methods for effective teaching. She is a fellow of INFORMS and of IISE.

INVITED GUESTS

DR. JEFFREY P. KHAROUFEH

PROFESSOR AND CHAIR
DEPARTMENT OF INDUSTRIAL ENGINEERING
CLEMSON UNIVERSITY

BIO

Jeff Kharoufeh is Professor and Chair of the Department of Industrial Engineering at Clemson University. He specializes in the application of probability and stochastic processes to the modeling, design, performance evaluation and optimal control of stochastic systems. His research focuses on energy systems, stochastic service systems, reliability theory and maintenance optimization. He earned a Ph.D. in Industrial Engineering and Operations Research at the Pennsylvania State University. Professor Kharoufeh currently serves as Area Editor for Operations Research Letters, Associate Editor for Operations Research and as a member of the Editorial Board for Probability in the Engineering and Informational Sciences. He is a Fellow of the Institute of Industrial and Systems Engineers (IISE) and a professional member of INFORMS and the Applied Probability Society (APS).

INVITED GUESTS

DR. JING LI

PROFESSOR
SCHOOL OF INDUSTRIAL AND SYSTEMS ENGINEERING
GEORGIA TECH

BIO

Jing Li is a Professor in the H. Milton Stewart School of Industrial and Systems Engineering at Georgia Tech. Prior to joining Georgia Tech in 2020, she was a Professor at Arizona State University and is a co-founder of the ASU-Mayo Clinic Center for Innovative Imaging.

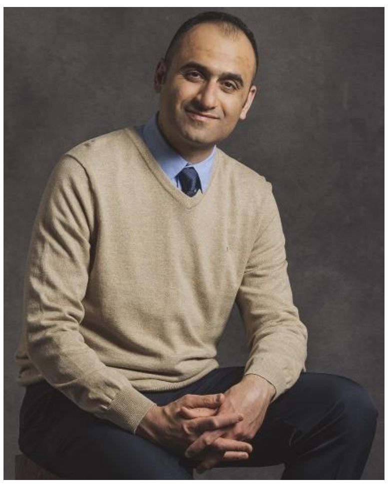
Dr. Li's research develops statistical machine learning algorithms for modeling and inference of medical image data, and fusion of images, genomics, and clinical records for personalized and precision medicine. Her research outcomes support clinical decision making for diagnosis, prognosis, and telemedicine for various conditions affecting the brain, such as brain cancer, post-traumatic headache & migraine, traumatic brain injury, and the Alzheimer's disease. Her research received Best Paper awards from various professional venues such as IISE Transactions, IISE Annual Conferences, INFORMS Data Mining and Decision Analytics, American Academy of Neurology, America Headache Society, etc. Her research has been funded by the NIH, NSF, DOD, and industries. She is an NSF CAREER Awardee.

Dr. Li is a former chairperson for the Data Mining Subdivision of INFORMS. She is currently the editor-in-chief for Quality Technology and Quantitative Management, an associate editor for IISE Transactions on Healthcare Systems Engineering, and an associate editor for IEEE Transactions on Automation Science and Engineering.

INVITED GUESTS

DR. ARMAN SABBAGHI

ASSOCIATE PROFESSOR
DEPARTMENT OF STATISTICS
PURDUE UNIVERSITY



BIO

Dr. Arman Sabbaghi is an Associate Professor in the Department of Statistics, and an Associate Director of the Statistical Consulting Service, at Purdue University. He received his PhD in Statistics from Harvard University in 2014, his AM in Statistics from Harvard University in 2011, and his BS in Mathematics (with Honors) and BS in Mathematical Statistics from Purdue University in 2009. Dr. Sabbaghi's research interests are in Bayesian data analysis, experimental design, and causal inference. Dr. Sabbaghi has received funding from the National Science Foundation, the National Institutes of Health, and Sandia National Laboratories. Dr. Sabbaghi's publications have appeared in statistics and engineering journals, such as the Annals of Applied Statistics, Biometrika, Statistical Science, Technometrics, IIE Transactions on Quality and Reliability Engineering, IEEE Transactions on Automation Science and Engineering, and Nano Energy. He has served as a reviewer for the National Science Foundation and multiple statistics and engineering journals.

INVITED GUESTS

DR. MURAT YILDIRIM

ASSISTANT PROFESSOR
DEPARTMENT OF INDUSTRIAL AND SYSTEMS ENGINEERING
WAYNE STATE UNIVERSITY

BIO

Dr. Murat Yildirim is an Assistant Professor in the Department of Industrial and Systems Engineering at Wayne State University. Prior to joining Wayne State, he worked as a postdoctoral fellow at the Georgia Institute of Technology (2016-2018). Dr. Yildirim's research interest lies in advancing the integration of mathematical programming and data analytics in various application domains. Specifically, he focuses on the modeling and the computational challenges arising from the integration of real-time inferences generated by advanced data analytics and simulation into large-scale mathematical programming models used for optimizing and controlling networked systems.

Student Participant

Current Affiliation

Ph.D. Candidate

Industrial Engineering

University of Pittsburgh

On Job Market

Advisor

Drs. Lisa Maillart and Oleg Prokopyev

Shadi Sanoubar

Introduction

My primary research interests are in sequential decision making under uncertainty, Markov decision processes, stochastic modeling, and applied probability, with focus on establishing theoretical properties of optimal policies and cost functions. My contributions have mainly been motivated by problems arising in maintenance optimization and reliability, yet I am also interested in applications in medical decision making and humanitarian logistics.

QSR Student Poster Competition, INFORMS 2020

Dynamic Repositioning of Condition-Based Maintenance Resources

Shadi Sanoubar, University of Pittsburgh, Department of Industrial Engineering
Joint work with Drs. Bram de Jonge (University of Groningen), Lisa Maillart, and Oleg Prokopyev
11/9/2020

Motivation

- Recent advances in sensor technologies facilitate the implementation of adaptive, condition based maintenance (CBM) policies
- In many CBM applications, the assets being maintained are **geographically dispersed** and the **maintenance resources are limited**

Self-propelled swimming robots used for maintaining subsea installations

SecondHands: a maintenance robot that offers help to maintenance technicians in fulfillment centers

Locomotive industry with assets distributed on a railroad network

Requires a novel framework to minimize costs by jointly optimizing the
- position of a maintenance resource
- timing of condition-based maintenance interventions

Research Problem

Formulate a Markov Decision Process (MDP) to obtain the optimal actions of a maintenance resource responsible for the maintenance activities of a set of geographically dispersed assets.

MDP	State	assets' deterioration conditions and maintenance resource position
	Actions	Idle, Travel, Repair
	Costs	down time, travel, repair
	Transition Probabilities	obtained from DTMCs

Findings

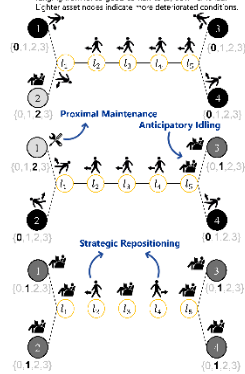
The MDP model enables us to study unique trade-offs:

Figure 1. Policy schematic for a single maintenance resource on a graph with four assets and five auxiliary locations. Each asset has four possible degradation levels ranging from (0) as-good-as-new to (3) down or failed. Lighter asset nodes indicate more deteriorated conditions.

Maintaining an asset earlier than we would for that asset in isolation (**Proximal Maintenance**)

Idling near the location of one asset even when another asset needs maintenance (**Anticipatory Idling**)

Repositioning even though no asset is yet in need of maintenance (**Strategic Repositioning**)

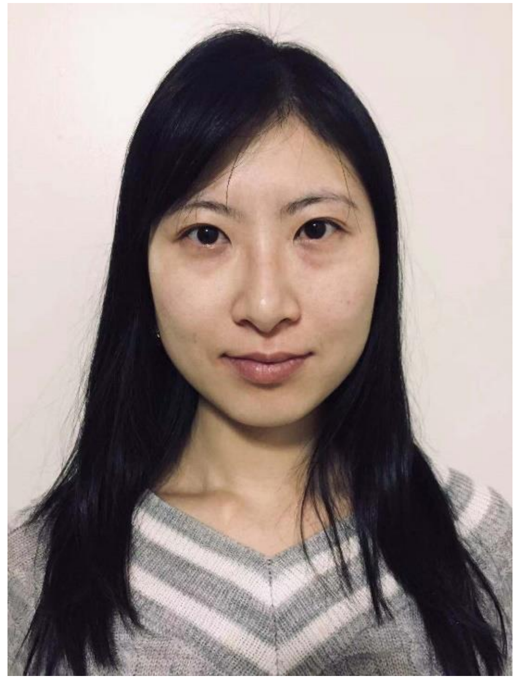


Additional Findings

- Structural properties of the optimal policies
- Quantifying several metrics of interest (e.g., percentage of time when idling is optimal) through simulation
- The effects of changes in parameter values (e.g., downtime, travel, or repair costs) on optimal policies and metrics
- Easy-to-implement heuristic policies

STUDENT PARTICIPANT

SHENGHAN GUO



CURRENT AFFILIATION

Ph.D. Candidate

Industrial and Systems Engineering

Rutgers University

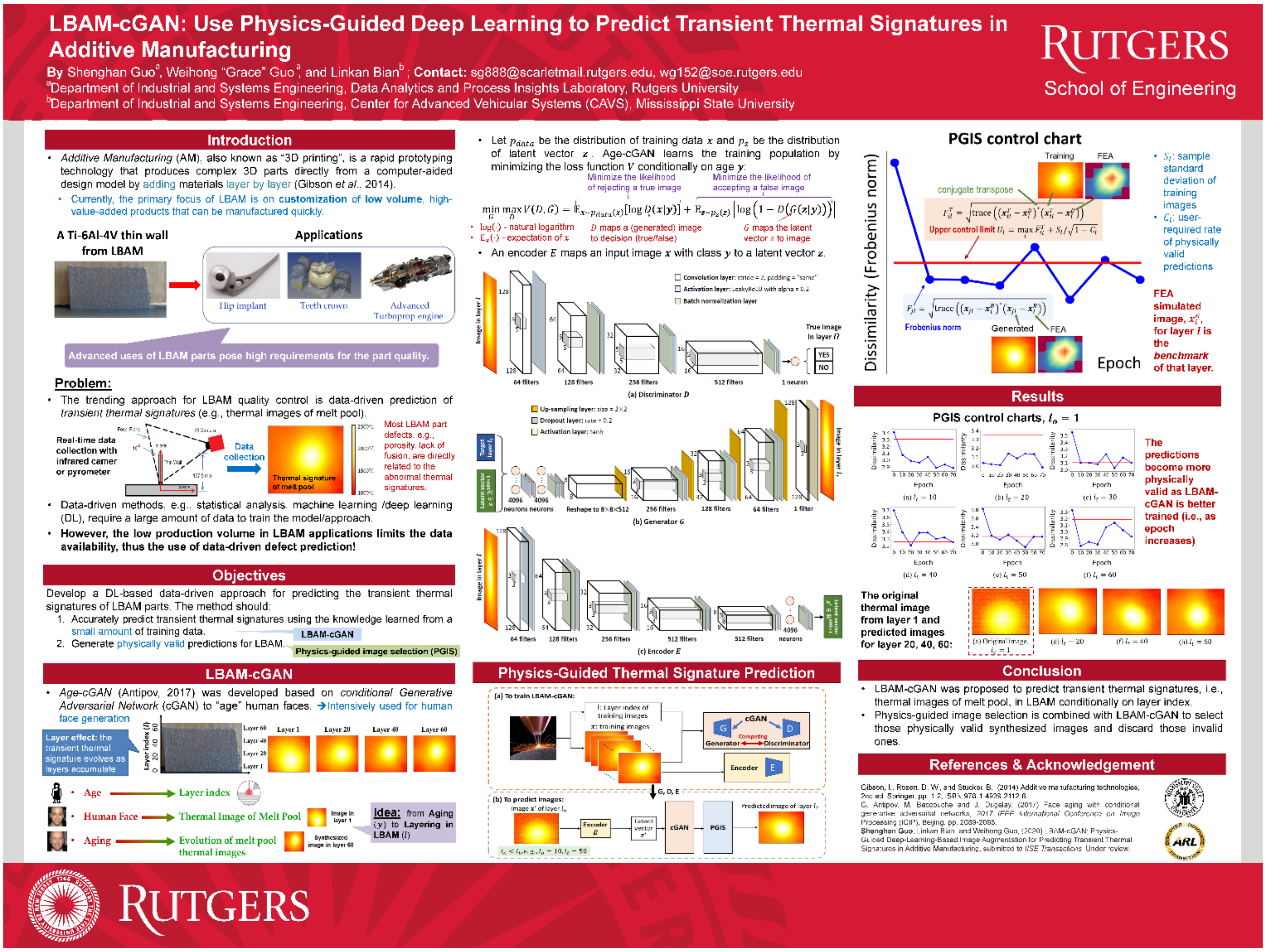
On Job Market

ADVISOR

Dr. Weihong (Grace) Guo

INTRODUCTION

My research focus on data-driven decision-making and predictive analytics. In-situ data from advanced manufacturing processes, e.g., laser-based additive manufacturing (AM), hot stamping, are complex. They may have high dimensionality and inter-attribute dependency or contain spatial-temporal correlations. To explore the decision-making value in these data, my research develops three branches of methods: (1) pattern recognition and analysis in multivariate times series for fault prediction, (2) spatial-temporal modeling and monitoring of AM thermal images for defect prediction, and (3) domain-knowledge-informed deep learning for defect prediction in AM with a small data amount. My research plan in near future is to expand my exploration in (3) and develop machine learning methods that integrates real data and expert/empirical knowledge for explainable learning process and prediction.



LBAM-cGAN: Use Physics-Guided Deep Learning to Predict Transient Thermal Signatures in Additive Manufacturing
By Shenghan Guo[a], Weihong "Grace" Guo[a], and Linkan Bian[b]; Contact: sg888@scarletmail.rutgers.edu, wg152@soe.rutgers.edu
[a]Department of Industrial and Systems Engineering, Data Analytics and Process Insights Laboratory, Rutgers University
[b]Department of Industrial and Systems Engineering, Center for Advanced Vehicular Systems (CAVS), Mississippi State University
RUTGERS
School of Engineering
Introduction
Additive Manufacturing (AM), also known as "3D printing", is a rapid prototyping technology that produces complex 3D parts directly from a computer-aided design model by adding materials layer by layer (Gibson et al., 2014).
Currently, the primary focus of LBAM is on customization of low volume, high-value-added products that can be manufactured quickly.
A Ti-6Al-4V thin wall from LBAM
Applications
Hip implant
Teeth crown
Advanced Turboprop engine
Advanced uses of LBAM parts pose high requirements for the part quality.
Problem:
The trending approach for LBAM quality control is data-driven prediction of transient thermal signatures (e.g., thermal images of melt pool).
Real-time data collection with infrared camer or pyrometer
Data collection
Thermal signature of melt pool
Most LBAM part defects, e.g., porosity, lack of fusion, are directly related to the abnormal thermal signatures.
Data-driven methods, e.g., statistical analysis, machine learning /deep learning (DL), require a large amount of data to train the model/approach.
However, the low production volume in LBAM applications limits the data availability, thus the use of data-driven defect prediction!
Objectives
Develop a DL-based data-driven approach for predicting the transient thermal signatures of LBAM parts. The method should:
1. Accurately predict transient thermal signatures using the knowledge learned from a small amount of training data.
2. Generate physically valid predictions for LBAM.
LBAM-cGAN
Physics-guided image selection (PGIS)
LBAM-cGAN
Age-cGAN (Antipov, 2017) was developed based on conditional Generative Adversarial Network (cGAN) to "age" human faces. → Intensively used for human face generation
Layer effect: the transient thermal signature evolves as layers accumulate
Layer index (l)
Layer 60
Layer 40
Layer 20
Layer 1
Layer 1
Layer 20
Layer 40
Layer 60
Age → Layer index
Human Face → Thermal Image of Melt Pool
Aging → Evolution of melt pool thermal images
Image in layer 1
Synthesized image in layer 60
Idea: from Aging (y) to Layering in LBAM (l)
Let p_{data} be the distribution of training data x and p_z be the distribution of latent vector z. Age-cGAN learns the training population by minimizing the loss function V conditionally on age y:
Minimize the likelihood of rejecting a true image
Minimize the likelihood of accepting a false image
$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim p_{data}(x)}[\log D(x|y)] + \mathbb{E}_{z\sim p_z(z)}\left[\log\left(1 - D(G(z|y))\right)\right]$
$\log(\cdot)$ - natural logarithm
$\mathbb{E}_x(\cdot)$ - expectation of x
D maps a (generated) image to decision (true/false)
G maps the latent vector z to image
An encoder E maps an input image x with class y to a latent vector z.
Convolution layer: stride = 2, padding = "same"
Activation layer: LeakyReLU with alpha = 0.2
Batch normalization layer
True image in layer l?
YES
NO
64 filters
128 filters
256 filters
512 filters
1 neuron
(a) Discriminator D
Up-sampling layer: size = 2×2
Dropout layer: rate = 0.2
Activation layer: tanh
4096 neurons
Reshape to 8×8×512
1 filter
(b) Generator G
(c) Encoder E
Physics-Guided Thermal Signature Prediction
(a) To train LBAM-cGAN:
l: Layer index of training images
x: training images
cGAN
Generator
Competing
Discriminator
Encoder
G, D, E
(b) To predict images:
Latent vector
PGIS
Predicted image of layer
PGIS control chart
Dissimilarity (Frobenius norm)
Training
FEA
conjugate transpose
Upper control limit
Frobenius norm
Generated
Epoch
S_l: sample standard deviation of training images
C_l: user-required rate of physically valid predictions
FEA simulated image, for layer l is the benchmark of that layer.
Results
PGIS control charts, $l_o = 1$
Epoch
Dissimilarity
The predictions become more physically valid as LBAM-cGAN is better trained (i.e., as epoch increases)
The original thermal image from layer 1 and predicted images for layer 20, 40, 60:
Conclusion
LBAM-cGAN was proposed to predict transient thermal signatures, i.e., thermal images of melt pool, in LBAM conditionally on layer index.
Physics-guided image selection is combined with LBAM-cGAN to select those physically valid synthesized images and discard those invalid ones.
References & Acknowledgement
Gibson, I., Rosen, D. W., and Stucker, B. (2014) Additive manufacturing technologies, 2nd ed. Springer, pp. 1-2, ISBN 978-1-4939-2112-6.
G. Antipov, M. Baccouche and J. Dugelay, (2017) Face aging with conditional generative adversarial networks, 2017 IEEE International Conference on Image Processing (ICIP), Beijing, pp. 2089-2093.
Shenghan Guo, Linkan Bian, and Weihong Guo, (2020) LBAM-cGAN: Physics-Guided Deep-Learning-Based Image Augmentation for Predicting Transient Thermal Signatures in Additive Manufacturing, submitted to IISE Transactions. Under review.
RUTGERS

Student Participant

Current Affiliation

Ph.D. Candidate

Industrial and Systems Engineering

Georgia Institute of Technology

On Job Market

Advisor

Dr. Kamran Paynabar

Ana Maria Estrada Gomez

Introduction

My research interests lie in developing efficient methodologies and algorithms for modeling and monitoring sensing systems with high-dimensional data, using statistics and machine learning tools. I focus on addressing analytical, computational, and scalability challenges associated with the study of interconnected systems with complex data structures. The methods I have developed have been applied in the manufacturing, service, and healthcare sectors.

I am passionate about teaching. My main goal is to have a positive impact on students' lives. I want them to learn how to use analytical tools and quantitative thinking for decision making.

I was recently appointed as a LATinE Fellow by Purdue´s College of Engineering, and I have been selected as a Graduate Teaching Fellow at Georgia Tech for two consecutive years.

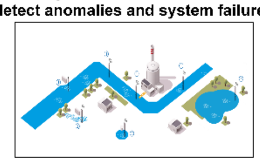
An Adaptive Sampling Strategy for Online Monitoring and Diagnosis of High-dimensional Streaming Data

Ana María Estrada Gómez, Dan Li, Kamran Paynabar

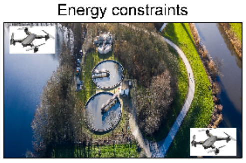
Georgia Tech ISyE Stewart School of Industrial & Systems Engineering

Motivation

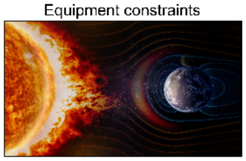
- **Complex systems** are continuously monitored by **hundreds of sensors** that provide a variety of **streaming data**.
- **Monitoring** such high-dimensional (HD) streaming data, **in real-time**, is critical to **detect anomalies and system failures.**



Environmental monitoring
Energy constraints



Spatial monitoring
Equipment constraints



Monitoring of streaming images
Processing & transmission constraints

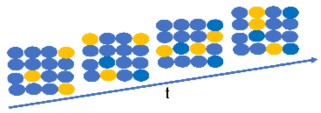
Challenges

- Incomplete data
- Spatial and temporal correlation
- Non-stationary data
- High-dimensional data streams

Objective

Develop an **adaptive sampling strategy** for real-time **monitoring** and **diagnosis** for **incomplete** and **non-stationary HD streaming data.**

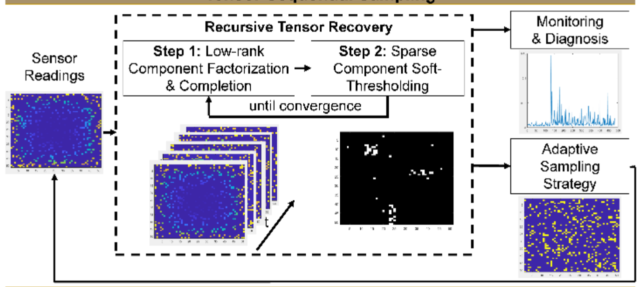
Problem Setting



- $I \times J$ variables distributed on a grid
- Due to resource constraints, for each t, only q data streams can be observed

Research questions:
- How to adaptively select observed variables at each time t?
- How to use the incomplete data to quickly detect a system change?
- How to determine where the system change occurred?

Tensor Sequential Sampling



Recursive Tensor Recovery Model

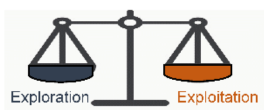
$$\mathcal{X}^{(t)} = \mathcal{L}^{(t)} + \mathcal{S}^{(t)} + \mathcal{E}^{(t)}$$

Low-rank component | Sparse component | Noise component

$$\min_{A^{(t)},B^{(t)},C^{(t)},\mathcal{S}^{(t)}} \frac{1}{2}\|\mathcal{W}^{(t)} * \mathcal{E}^{(t)}\|^2 + \lambda \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=t-T}^{t} w_{i,j,k}|s_{i,j,k}|$$

$$\text{s.t.} \quad \mathcal{W}^{(t)} * \mathcal{X}^{(t)} = \mathcal{W}^{(t)} * \left([\![A^{(t)}, B^{(t)}, C^{(t)}]\!] + \mathcal{S}^{(t)} + \mathcal{E}^{(t)} \right)$$

Adaptive Sampling



$$\beta p_t^{exploration}(i,j) + (1-\beta) p_t^{exploitation}(i,j)$$

Monitoring and Diagnosis

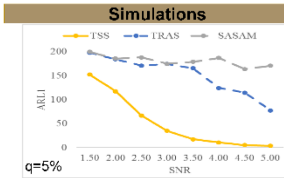
Monitoring: EWMA control chart

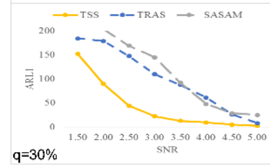
$$\boxed{y_t = \sum_{i=1}^{I}\sum_{j=1}^{J} |\hat{s}_{i,j,t}|}$$

Recursive Diagnosis

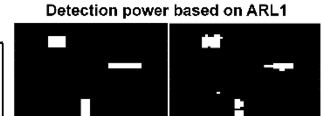
1. Average of the sparse component
2. Smooth the average
3. Use soft-thresholding for estimation

Simulations



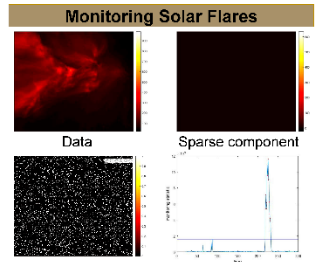


Detection power based on ARL1



Detected anomalies

Monitoring Solar Flares



Contributions

We developed a **tensor sequential sampling algorithm** for **online monitoring** and **diagnosis** of **HD streaming data.**

Student Participant

Arvind Krishna

Current Affiliation

Ph.D. Candidate

Industrial and Systems Engineering (ISyE)

Georgia Institute of Technology

On Job Market

Advisor

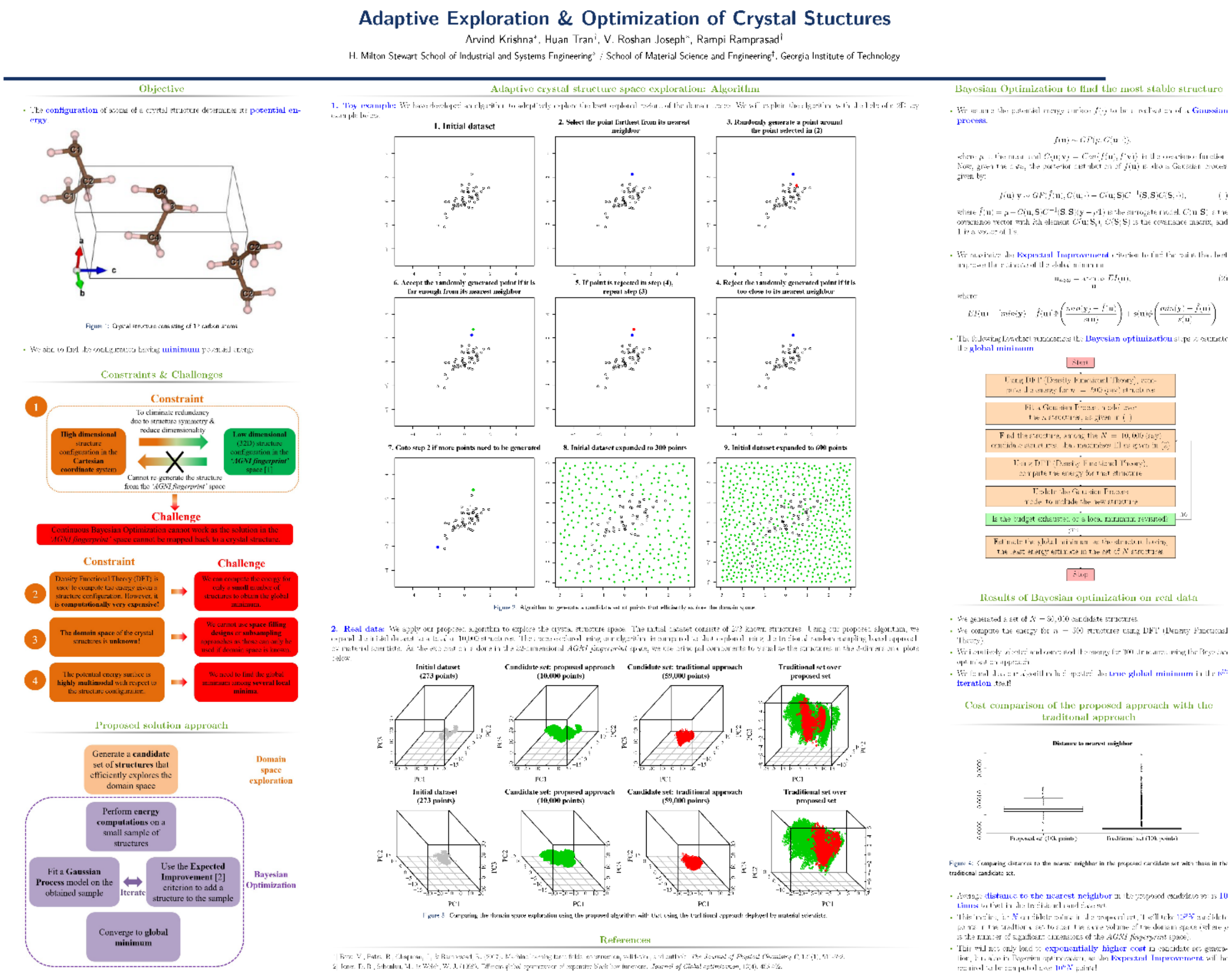
Dr. Roshan Joseph

Introduction

I am interested in applied research in the field of data science and machine learning. I have developed novel statistical methods for big data reduction and big data exploration. I have also worked on experimental design problems to maximize information gain from small, but expensive data. My paper on 'Robust experimental designs for model calibration' is under review in the Journal of Quality Technology. In my INFORMS talk, I will present a method to generate a space-filling design, without knowing the boundaries of the domain space.

I love teaching, and try novel ways to make the courses exciting and stimulate student interest. I taught an introductory course on Probability and Statistics (ISyE 3770) to undergraduates in summer 2020. I used everyday examples to explain statistical concepts. My students, and the Georgia Tech faculty appreciated my efforts in ensuring high class engagement, despite the online teaching environment due to COVID-19.

informs. QUALITY, STATISTICS & RELIABILITY



STUDENT PARTICIPANT

CURRENT AFFILIATION

Ph.D. Candidate

Industrial and Systems Engineering

University at Buffalo

On Job Market

ADVISOR

Dr. Hongyue Sun

LUIS JAVIER SEGURA

INTRODUCTION

Luis Javier Segura's research interest focuses on high-dimensional data-driven quality control in inkjet 3D printing (IJP). In his first two-year of Ph.D., he has been working on the IJP from (1) online change detection of droplet jetting, (2) spatial-temporal dynamics learning and forecasting of droplet evolution, to (3) tensor response physical model emulation of solidification, to systematically investigate and guarantee the IJP process quality. He has published in total 3 journal papers in Additive Manufacturing, ASME JCISE, etc., and 4 conference papers in MSEC, etc. He was a recipient of Fulbright Scholarship, UB presidential fellowship, first place of UB ISE poster competition, and honorable mention of UB ISE researcher of the year.

Unsupervised Learning for the Droplet Evolution Prediction and Process Dynamics Understanding in Inkjet Printing

University at Buffalo

Jida Huang[a], **Luis Javier Segura**[b], Tianjiao Wang[b], Guanglei Zhao[b], Hongyue Sun[b], and Chi Zhou[b]

[a]Department of Mechanical and Industrial Engineering, University of Illinois at Chicago

[b]Department of Industrial and Systems Engineering, University at Buffalo

UIC UNIVERSITY OF ILLINOIS CHICAGO

I. Motivation, Objective, and Approach

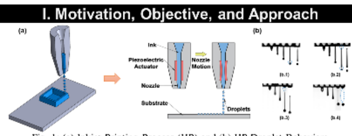


Fig. 1: (a) Inkjet Printing Process (IJP) and (b) IJP Droplet Behaviors

Motivation

- In the inkjet printing (IJP) process (Fig. 1 (a)), the fluid flow pattern (Fig. 1 (b)) governs the droplet evolution behavior and its quality.
- Capturing the spatio-temporal relationships of the various droplet evolution behaviors is critical to the process monitoring and control.
- Videos capture these relationships and are difficult to label.

Objective

- To propose an unsupervised learning method to study the flow pattern of the droplet evolution from unlabeled IJP videos.

Challenges

- How to learn the spatio-temporal relationships from the IJP videos.
- How to deal with the unlabeled data and learn the process dynamics.

Approach

- We implement a deep recurrent neural network (DRNN) to learn the latent representation and infer the forming stimulus of the droplets.

II. State-of-the-Art

In-situ Monitoring in IJP

- IR, accelerometer, etc. have been used (Rao *et al.*, 2015, etc.).
- Machine vision systems via cameras (Wang *et al.*, 2019, etc.).

Machine Learning Methods for Process Monitoring in AM

- Supervised: anomaly detection via CNN (Scieme *et al.*, 2018).
- Semi-supervised: defect classification via SVD (Okaro *et al.*, 2019).
- Unsupervised: it is limited in the literature (Stetco *et al.*, 2019).

III. Methodology

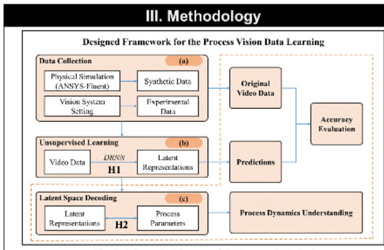


Fig. 2: Schematic Diagram of the Proposed Method

Methodology

Data Collection (Synthetic data)

- The Navier-Stokes equations govern the mass and momentum conservation for the liquid-gas interface (Fig. 3 (a)).

Mass conservation $\nabla \cdot \boldsymbol{u} = 0$

Momentum conservation $\rho\left[\frac{\partial \boldsymbol{u}}{\partial t} + (\boldsymbol{u} \cdot \nabla)\boldsymbol{u}\right] = \nabla\sigma + f$

Data Collection (Experimental data)

- The hardware of the video collection system is shown in Fig. 3 (b), and the video resolution is $640 \times 480\ pixels$.

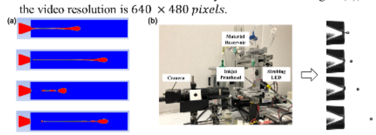


Fig. 3: (a) Simulated Data and (b) IJP Setup and Experimental Data

Unsupervised Learning

- **H1:** with a DRNN, a latent representation of the videos can be learned and predictions can be made (Fig. 2 (b)).
- **PredNet** (Lotter *et al., 2016)* is used to implement the DRNN (Fig. 4).

Latent Space Decoding

- **H2:** the learned representation can be related to the droplet evolution stimulus parameters and supports dynamics understanding (Fig. 2 (c)).
- Stimulus parameters can be material properties (e.g., viscosity) and process settings (e.g., back-pressure).

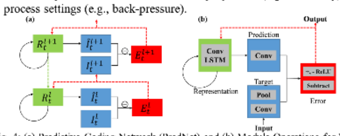


Fig. 4: (a) Predictive Coding Network (PredNet) and (b) Module Operations for Videos

IV. Experimental Results

Protocol

- IJP simulated (1800 videos) and experimental (4500 videos) data were collected (Fig. (3)).
- Three parameters (Table 1) that affect the droplet evolution were investigated for the simulated data.
- For the DRNN, the number of layers were set to $L = 4$ and $L = 5$ for simulated and experimental data, respectively.

Table 1: Ranges of the Solution/Ink for Video Generation

Material Properties	Low Level	High Level
Density $\left({}^{kg}/_{m^3}\right)$	800	8000
Viscosity $\left({}^{kg}/_{m \cdot s}\right)$	0.0005	0.15
Surface Tension $\left({}^{dyn}/_{cm}\right)$	50	80

Experimental Results

- The filter size was set as 3×3 and max-pooling stride at 2.
- The number of filters for R^l and I^l are both set as $(3, 48, 96, 192)$ for the simulated data and $(1, 32, 64, 128, 256)$ for the experimental data.
- Prediction model accuracy was assessed via Mean Square Error (MSE) and structure similarity index measure (SIMM) (Figs. 5 (a-c)).
- The latent decoding performance was computed for different layer weight-scenarios (Fig. 5 (d)).
- The results for simulated and experimental videos are shown in Fig. 5.

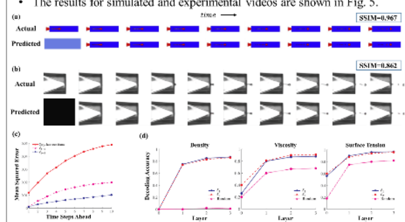


Fig. 5: (a) Simulated One-step Ahead Prediction, (b) Experimental One-step Ahead Prediction, (c) MSE Comparison of Multi-step Predictions, and (d) Decoding Accuracy

V. Conclusions and Future Work

Conclusions

- The droplet flow pattern and underlying dynamics are studied via an unsupervised learning framework.
- The framework successfully predicts the droplet behaviors and decodes the forming stimulus parameters.

Future Work

- Utilize the learned features for process parameters adjustment.
- Deploy the proposed framework in real-time monitoring and control of IJP.

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DI LIU

INTRODUCTION

My research consists on quality engineering and stochastic process. I am interested in learning and applying knowledge from operations research and statistics to question and challenge fundamental assumptions in quality and operations engineering in order to improve manufacturing processes.

I am currently working on the research of double tolerance design in stochastic production environment. It is the first to introduce the concept of double tolerance sets to the tolerance design optimization literature. By comparing with a traditional single tolerance model, the model with double tolerance schemes is more cost-effective and can be used to decide when to rework or scrap a product in the process. I am also interested in using the double tolerance schemes to solve refurbishing problems which will be presented in Informs Annual Conference 2020.

CLEMSON UNIVERSITY

Double Tolerance Design for Manufacturing Systems

Di Liu, Tugce Isik, B. Rae Cho, Clemson University

CLEMSON INDUSTRIAL ENGINEERING

1. Abstract

Tolerance design techniques are widely used for manufacturing processes. It is the first to introduce the concept of double tolerance sets to the tolerance design optimization literature. By comparing with a traditional single tolerance model, the model with double tolerance schemes is more cost-effective and can be used to decide when to rework or scrap a product in the process.

Keywords: Quality control; Double tolerance; Rework queue; General service times; Nonlinear programming.

3. Problem Description

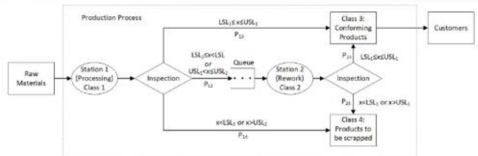


Figure 1: System boundaries of double tolerance optimization

4. Methods

A nonlinear optimization model is developed for determining tolerance sets (Δ_1 and Δ_2) to maximize the long-run average net profit (y).

We incorporate the following features into comprehensive tolerance optimization models:

- the double tolerance system
- uncertainty in the production system
- truncated process distributions
- imperfect reworking

2. Double Tolerance vs. Single Tolerance

Tolerance is defined as the permissible distance from the lower specification limit to the upper specification limit in the measured value of the quality characteristic.

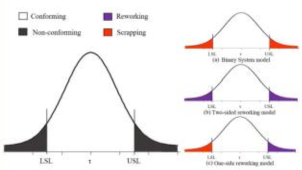


Figure 2: Single tolerance models

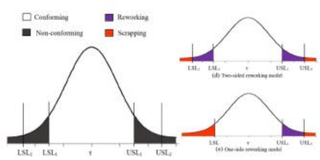


Figure 3: Double tolerance models

We refer to the models with only one tolerance set as the single tolerance models (see Fig. 2).
We investigate the double-tolerance models (see Fig. 3) with inner and outer tolerances.
There are 3 possible product classifications:

- conforming products
- nonconforming products to be reworked
- nonconforming products to be scrapped

Setting outer tolerances to separate the nonconforming products into two groups can be cost-effective.

5. Results

We investigate the concavity of the objective function for both double and single tolerance models.

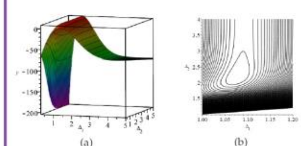
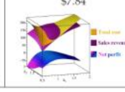
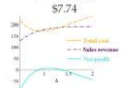


Figure 4: (a) 3d plot and (b) contour plot of y for the double tolerance model in the example

For the double tolerance model, there exist a maximum y with optimal tolerances and a limit of y as the tolerances tend to infinity.
Results of a numerical example comparing the single and double tolerance models is summarized in Table 1.

Table 1: Example computational results

	Double tolerance model	Single tolerance model
Δ^*	$\Delta_1^* = 1.077, \Delta_2^* = 2.201$	$\Delta^* = 1.091$
y^*	\$7.84	\$7.74
plots		

In addition, we run an extensive sensitivity analysis and examine the impact of relaxing our assumptions. The results show that the double tolerance model could outperform the single tolerance model in terms of profits, and be more cost-effective in a variety of settings.

6. Contributions

The main contribution of this study is three-fold:

- The double tolerance scheme with triple product classification is introduced.
- The traditional tolerance design problem is extended to account for stochastic environments.
- The actual truncated distribution for conforming products is used.

References

[1] S Shin and B R Cho. Integrating a bi-objective paradigm to tolerance optimization. *International Journal of Production Research*, 45(23):5509–5525, 2007.

7. Future Research

- Remanufacturing Process Design using Double Tolerance Schemes
- Double Tolerance Design for A Product Family

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Introduction

My research interests are in the areas of quality engineering, machine learning, and statistics. I am especially interested in (1) System degradation modeling and prognostics, (2) Bayesian deep learning including Gaussian processes and Bayesian neural networks, and (3) Hybrid prognostic approaches integrating domain knowledge-based and data-driven methods.

My research has focused primarily on advanced manufacturing and healthcare. I'm currently studying new methodologies to open an entire field of novel applications for degradation modeling and prognostics, ranging from materials in nuclear applications to general soft matter systems.

A Variational Bayesian Neural Network Framework for Interval Estimation of System Failure Time

Minhee Kim (mkim555@wisc.edu) and Kaibo Liu
Department of Industrial and Systems Engineering, University of Wisconsin-Madison

1. Background

State-of-art Neural network-based prognostic methods

$\boldsymbol{x}$: Observed Degradation Signals → Neural Network → y: Failure Time

Focus: Types of networks & Design of outputs
Flexibility & High prognostic accuracy

2. Research Gap

Purely data-driven providing only point estimations of failure time

➔ Lack of interpretability & Wrong decision-making
- "How reliable is this failure time prediction?"
- "Do we need more data?"
- "Do we need to be more cautious when making risk analysis or maintenance decision?"

3. Objective

To establish the first variational Bayesian framework enhancing interpretability and practicality of neural network prognostic models by
- Uncertainty quantifications of failure time prediction
- Considering characteristics of degradation processes
  - Stochasticity, data limitedness, etc.

4. Two types of Uncertainty in Prognostics

Estimate failure time y based on degradation signals $\boldsymbol{x}$

$$y = f^{\boldsymbol{W}}(\boldsymbol{x}) + \varepsilon, \qquad \varepsilon \sim N(0, \sigma^2)$$

Degradation Uncertainty	Uncertainty from stochastic nature of degradation process captured by σ^2

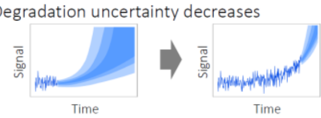
- system-to-system variability
- signal measurement error

Model Uncertainty	Uncertainty in parameter $\boldsymbol{W}$

- limited data availability
- new type of systems in test set → unusual $\boldsymbol{x}$

5. Methodology

- Degradation Uncertainty
  - Monotonic relationship; Approaches failure (Remaining Lifetime decreases)
    ➔ Degradation uncertainty decreases



- Model Uncertainty
  - Bayesian Inference + Neural Network

$$p(\boldsymbol{W}|D) = \frac{p(D|\boldsymbol{W})\boxed{p(\boldsymbol{W})}}{p(\boldsymbol{W})}$$

  - Predict failure time y^* for new signal $\boldsymbol{x}^*$

$$p(y^*|\boldsymbol{x}^*) = \int p(y^*|\boldsymbol{x}^*, \boldsymbol{W})p(\boldsymbol{W}|D)d\boldsymbol{W}$$

  - Challenge: exact Bayesian inference is computationally intractable
  - MC Dropout: approximate $p(\boldsymbol{W}|D)$ with variational distribution $q(\boldsymbol{W})$
- Interval Estimation of System Failure Time
  - Estimate $q(y^*|\boldsymbol{x}^*)$ using R Monte Carlo samples:

$$E_{q(y^*|\boldsymbol{x}^*)}(y^*) \approx \frac{1}{R}\sum_{r=1}^{R} p(y^*|\boldsymbol{x}^*, \widehat{\boldsymbol{W}}_r) = \frac{1}{R}\sum_{r=1}^{R} f^{\widehat{\boldsymbol{W}}_r}(\boldsymbol{x}^*)$$

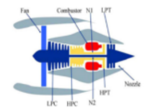
$$Var_{q(y^*|\boldsymbol{x}^*)}(y^*) \approx \hat{\sigma}^2 + \overset{\text{Second moment}}{\overline{\frac{1}{R}\sum_{r=1}^{R}\left(f^{\widehat{\boldsymbol{W}}_r}(\boldsymbol{x}^*)\right)^2}} - \left(\overset{\text{First moment}}{\overline{\frac{\sum_{r=1}^{R} f^{\widehat{\boldsymbol{W}}_r}(\boldsymbol{x}^*)}{R}}}\right)^2$$

Estimated degradation uncertainty

Estimated model uncertainty (sample variance)

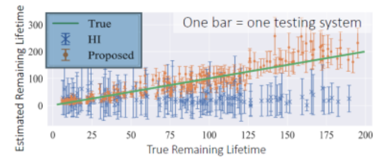
6. Application

- f: Bayesian LSTM
- Turbofan Aircraft Engine

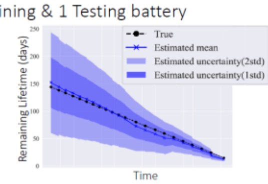


  - 21 Sensors
  - 3 Environmental variables
  - 6 Environmental conditions
  - 2 Failure modes
  - 248 Training & 248 Testing engines
  - Failure Time prediction error (RMSE)

Proposed	LSTM	DCNN	MODBNE	HI
19.41	29.78	29.16	28.66	75.78



- Li-ion battery
  - 3 Sensors
  - 3 Training & 1 Testing battery



7. Summary

- Modeling two types of uncertainties in degradation modeling and prognostics
  - General characteristics of degradation processes
  - Variational Bayesian inference

➔

- Wide applicability
- Robust to overfitting
- Probabilistic interpretability
- High accuracy

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Introduction

My research area includes machine learning with special focus on Gaussian process, sequential design, uncertainty quantification and non-linear dynamic systems.

Generalized Polynomial Chaos-informed Efficient Stochastic Kriging

Yiming Che, Ziqi Guo and Changqing Cheng

Department of Systems Science and Industrial Engineering

State University of New York at Binghamton, Binghamton NY 13902

Abstract

Stochastic kriging (SK) offers an explicit way to characterize heterogeneous noise variance in stochastic computer simulations and has gained considerable traction recently as a surrogate model. Nevertheless, SK relies on tedious Monte Carlo (MC) method to estimate the intrinsic variance at each design input. For computationally expensive simulations, the substantial replication effort has essentially rendered SK intractable. To this end, we develop generalized polynomial chaos (GPC)-informed efficient stochastic kriging (GPC-SK) to ameliorate the computational cost. At its core, GPC supplants the tedious repetitive MC simulations, instead resting on a much smaller set of sampling points to estimate the intrinsic uncertainty, thus applicable to those prohibitively expensive simulations.

Introduction of SK

- **SK extends the conventional kriging model to delineate the response surface in stochastic simulation**
  - the output of j^{th} replication of the simulation

$$\mathcal{Y}_j(x) = Y(x) + \varepsilon_j(x)$$

  - ε_j: the sampling noise that $\varepsilon_j \sim N(0, V(x))$
  - V: the intrinsic uncertainty
  - Y: the true mean at $\boldsymbol{x}$
- Y is regarded as the universal kriging

$$Y(x) = \boldsymbol{f}(x)^T\boldsymbol{\beta} + M(x)$$

  - $\boldsymbol{f}(x)^T\boldsymbol{\beta}$ captures the trend with $\boldsymbol{f}(x)$ a set of pre-defined basis
  - $M(x): \mathbb{R}^d \rightarrow \mathbb{R}$ is a second-order stationary zero-mean Gaussian random field
- **Assumptions**
  - The random field M, which captures the extrinsic uncertainty or the random variation of the response surface around the trend, is a zero-mean stationary Gaussian random field.
  - $\varepsilon_1(\boldsymbol{x_i}), \varepsilon_2(\boldsymbol{x_i}), \ldots$ follows identical and independent distribution $N(0, V(\boldsymbol{x_i}))$ and captures the intrinsic uncertainty. They are also independent of $\varepsilon_j(\boldsymbol{x_k})$ for all j and $k \neq i$ and independent of M.
- **The mean response**

$$\bar{\mathcal{Y}}(x_i) = \frac{1}{n_i}\sum_{j=1}^{n_i}\mathcal{Y}_j(x_i) = Y(x_i) + \bar{\varepsilon}(x_i)$$

- **The linear predictor**
  - $\hat{Y}(\boldsymbol{x_0}) = \lambda_0(\boldsymbol{x_0}) + \boldsymbol{\lambda}(\boldsymbol{x_0})^T\bar{\boldsymbol{\mathcal{Y}}}$
  - Minimize MSE $\left[\left(Y(\boldsymbol{x_0}) - \hat{Y}(\boldsymbol{x_0})\right)^2\right]$
    - $\lambda_0 = \boldsymbol{f}(\boldsymbol{x_0})^T\boldsymbol{\beta} - \boldsymbol{\lambda}^T\boldsymbol{1}_N(\boldsymbol{f}(\boldsymbol{x_0})^T\boldsymbol{\beta})$
    - $\boldsymbol{\lambda} = [\Sigma_M + \Sigma_\varepsilon]^{-1}\Sigma_M(\boldsymbol{x_0}, \boldsymbol{X})$

Simulation Budget of SK

- **Estimation of intrinsic variance V**

$$\hat{V}(x_i) = \frac{1}{n_i - 1}\sum_{j=1}^{n_i}\left(\mathcal{Y}_j(x_i) - \bar{\mathcal{Y}}(x_i)\right)^2$$

  - n_i simulations are required for each design point $\boldsymbol{x}$
  - n_i is usually large!
  - Not affordable for large-scale or expensive-to-evaluate stochastic systems

GPC-SK

- **How to save simulation budget?**
  - We place another surrogate model for $\mathcal{Y}_j(\boldsymbol{x})$

$$\mathcal{Y}_j(x) = Y_j^{pc}(x) + \epsilon_j(x)$$

  - $\epsilon_j(\boldsymbol{x})$: the bias
  - $Y_j^{pc}(\boldsymbol{x})$: the GPC surrogate model
  - Usually needs a small number of simulation budget for fitting
- **GPC surrogate model**

$$\boldsymbol{\mathcal{Y}} = \boldsymbol{\Phi}_f\boldsymbol{\alpha} + \boldsymbol{\epsilon}$$

$$\hat{\boldsymbol{\alpha}} = \arg\min_{\alpha}\left\|\boldsymbol{\mathcal{Y}} - \boldsymbol{\Phi}_f\boldsymbol{\alpha}\right\|_2$$

  - n_f simulations for fitting at each design point $\boldsymbol{x}$
  - n_f is usually much smaller
- **Estimation of the bias**
  - bias $\epsilon_j(\boldsymbol{x}) \sim N(\mu(\boldsymbol{x}), \mathcal{V}(\boldsymbol{x}))$
  - $\epsilon_j(\boldsymbol{x})$ not necessary to be zero-mean
  - Leave-one-out technique
  - Almost unbiased estimation
- **The mean response**

$$\bar{Y}^{pc}(x) = \frac{1}{n_t}\sum_{j=1}^{n_t}Y_j^{pc}(x) = Y(x) + \bar{\varepsilon}(x) - \bar{\epsilon}(x)$$

  - After GPC is built, do another n_t simulations in GPC surrogate model
  - n_t is usually very large
  - Why? Eliminate sampling uncertainty
- **The linear predictor**
  - $\hat{Y}^{pc}(\boldsymbol{x_0}) = \lambda_0(\boldsymbol{x_0}) + \lambda(\boldsymbol{x_0})^T\bar{\boldsymbol{Y}}^{pc}$
  - Minimize MSE $\left[\left(Y(\boldsymbol{x_0}) - \hat{Y}(\boldsymbol{x_0})\right)^2\right]$
    - $\hat{Y}^{pc}(\boldsymbol{x_0}) = \boldsymbol{f}(\boldsymbol{x_0})^T\boldsymbol{\beta} + \Sigma_M(\boldsymbol{x_0}, \boldsymbol{X})^T[\Sigma_M + \Sigma_\epsilon]^{-1}(\bar{\boldsymbol{Y}}^{pc} + \hat{\boldsymbol{\mu}} - \boldsymbol{F\beta})$
    - $MSE\left(\hat{Y}^{pc}(\boldsymbol{x_0})\right) = \Sigma_M(\boldsymbol{x_0}, \boldsymbol{x_0}) - \Sigma_M(\boldsymbol{x_0}, \boldsymbol{X})^T[\Sigma_M + \Sigma_\epsilon]^{-1}\Sigma_M(\boldsymbol{x_0}, \boldsymbol{X})$
- **One more assumption**
  - $\epsilon_1(\boldsymbol{x_i}), \epsilon_2(\boldsymbol{x_i}), \ldots$ are i.i.d. $N(\mu(\boldsymbol{x_i}), \mathcal{V}(\boldsymbol{x_i}))$, independent of $\epsilon_j(\boldsymbol{x_k})$ for all j and $k \neq i$, and independent of M and ε
- **Estimation of bias mean and variance is the key part of GPC-SK**
  - It directly affects the predictor $\hat{Y}^{pc}(\boldsymbol{x_0})$

Flowchart of GPC-SK

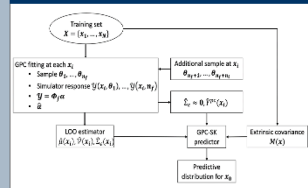

Figure 1 Flowchart of GPC-SK

Case Study: Stability Identification of Time-delay Dynamic Systems

- **Characterize the vibration in the feed direction via a second-order delay differential equation**

$$\ddot{z}(t) + 2\zeta\omega_n\dot{z}(t) + \omega_n^2 z(t) = -\mathcal{K}w\left(x_1 - z(t) + z(t-\tau)\right)$$

  - State variable z denotes the tool displacement in feed direction during vibration
  - Uncertainty exists in the process parameters
    - Natural frequency $\omega_n \sim N(600\pi, (3\pi)^2)(\mathrm{Hz})$
    - Damping ratio $\zeta \sim N(0.02, 0.01^2)$
    - Force coefficient $\mathcal{K} \sim N\left(2 \times 10^{11}, 10^2\right) N/m^2$
  - The design variable x_1 (μm) is the nominal feed rate
  - The time delay τ is explicitly determined by another design variable, the spindle speed x_2, as $\tau = \frac{2\pi}{x_2}$
- **Target: detect the boundary that separate stable and unstable cutting area**
  - Based on TFEM method with Hermite basis functions. It can be rewritten in a compact matrix form

$$\boldsymbol{N}\boldsymbol{a}^n = \boldsymbol{P}\boldsymbol{a}^{n-1} + \boldsymbol{Q}$$

  - Stability is determined by the eigenvalue of $\boldsymbol{G} = \boldsymbol{N}^{-1}\boldsymbol{P}$
  - $\lambda_G < 1$ for stable area
  - Hence, find the contour that $\lambda_G = 1$

Sequential Design

- **Why Sequential Design?**
  - In many real-world cases, the quantity of interest is only a certain level of response value instead of all of them.
  - Very slow to explore all the design space
- **The design is based on the classic trade-off between exploration and exploitation, which strive for the local accuracy not global accuracy**

$$U(x^*|X) = \max_{x^*}\left(0, \Delta - \left|y_0 - \hat{Y}^{pc}(x^*)\right|\right)$$

Results

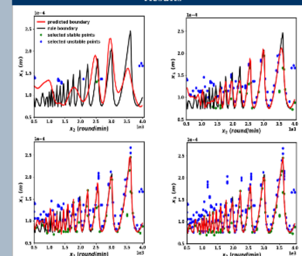

Figure 2 GPC-SK sequential optimal design

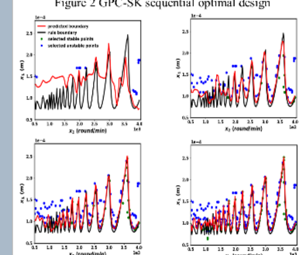

Figure 3 SK sequential optimal design

Analysis

- **Why SK doesn't fit as well as GPC-SK?**
  - Lack of replications
    - Large intrinsic variance !
    - Too smooth
    - Inaccurate estimation of responses misguided exploration of sequential design
  - Improve?
    - Increase simulation budget
    - Hence, using GPC-SK is a better choice!

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JINGWEN XUE

INTRODUCTION

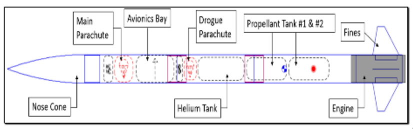
My research interest is design and analysis of rocket performance using statistical methods.

Discovering the Beyond: A Design and Analysis of Morgan State University's Liquid Propellant Rocket (LPR)

Jingwen Xue[1,4], Marc J Louise Caballes[1,3], Margaret Ajuwon[1,3], Samuel Oludayo Alamu[1,3] and Guangming Chen[2,3]
[1]Graduate Student, [2]Professor, [3]Department of Industrial and Systems Engineering, [4]Department of Civil Engineering

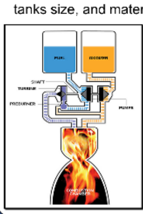
Background

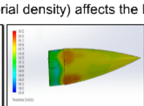
- Morgan State University (MSU) received a grant award last year from BASE 11 to build and launch a Liquid Propellant Rocket (LPR) and develop the first Aerospace and Rocketry Program (ARP) at an HBCU.
- Designing and printing 3D-Models before the actual fabrication of the rocket allows students and staffs to create high-quality prototypes, run simulations, and efficiently identify errors in both dimensions and designs.
- Reliability and validity plays a vital role for consistency and accuracy of the experiment during the design and simulation phase of the rocket.

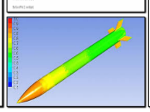


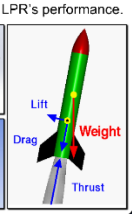
Research Objectives

- To design and model the necessary components of the external and internal parts of the rocket.
- To check the consistency and effectiveness of the designed LPR when placed under the same environment and circumstances during simulation.
- To analyze how the factors (e.g., airframe length, propellant tanks size, and material density) affects the LPR's performance.

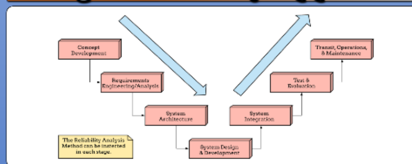


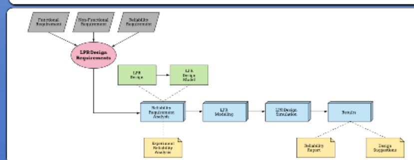




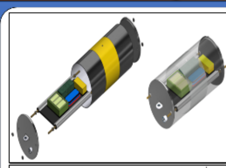


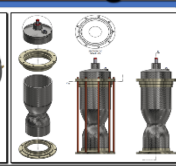
Design Reliability Approach

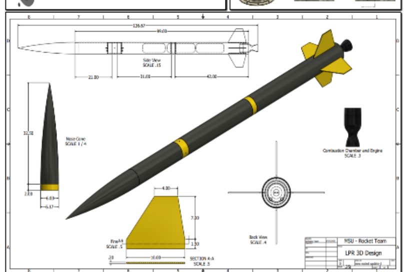




2D and 3D Modeling



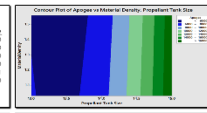


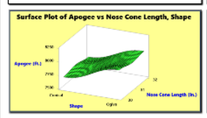


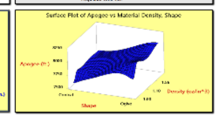
Results and Discussion

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	6	1160416	193403	231.31	0.000
Linear	6	1160416	193403	231.31	0.000
Shape	1	737022	737022	881.48	0.000
Material Density	2	353128	176564	211.17	0.000
Nose Cone Length	1	3823	3823	4.57	0.041
Nose Cone Diameter	2	66442	33221	39.73	0.000
Error	29	24247	836		
Total	35	1184663			







- From the simulated result, the highest apogee of 17,975ft was achieved at LPR nose cone of 35 inches, 88 inches airframe length, 15 inches propellant tanks, and carbon fiber material.
- Analysis of Variance (ANOVA) results showed both material density, airframe length and propellant tank size are significant factors on apogee as well as the height of the nose cone.

Conclusion

- Reliability analysis method was applied in product development process (design and modeling process of the LPR).
- Design for reliability approach is used to analyze and determine the major inner (e.g., GPS, DAQ) and outer components (e.g., nose cone, airframe).
- Simulation analysis and the factorial design were performed to get the best design setting of material selection, and to assure the mission reliability achieve the design requirement of at least 13,000 feet of the LPR apogee.

References

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2. Nilsen, C., Meyer, S., & Meriam, S. (2019). Purdue Liquid Oxygen-Liquid Methane Sounding Rocket. In AIAA Scitech 2019 Forum (p. 0614).
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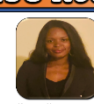
MSU Rocket Team



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Marc J Louise Caballes

Introduction

I am one of the Project Leads of the Base 11 Rocketry at Morgan State University, where the team and I design and fabricate the first-ever university rocket at MSU. Aside from that, the research area that I am interested in is utilizing Mixed Reality (MR) technologies, including Virtual Reality and Augmented Reality, in any field – Industry or Academia. Additionally, I want to uncover its limitations and improve it by taking it beyond its capabilities.

Furthermore, I believe that if MR is used correctly, it can drastically improve present educational and training opportunities that are not possible with traditional instruction methods and other mediums, like online videos. MR allows users to experience high-fidelity environments and situations that would ordinarily be dangerous to learn. As we adapt to the new norm right now that is brought by this pandemic, the usage of MR will not deteriorate the learning experience of students even if everything is virtual.

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MARGARET AJUWON

INTRODUCTION

I am fascinated by Engineering optimization models and applying them to various problems in different stages of complex multi-echelon supply chain.

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SAMUEL OLUDAYO ALAMU

INTRODUCTION

My research interest focuses on Process Control and Dynamics, Process Design and Optimization, Big data analysis using AI tools among others, for manufacturing processes. I have led a team of students to develop a feedback control system for our lab-scale fluidized bed combustion system using Programmable Logic Controller (PLC). I have conducted some research works on converting high volume waste (biomass) to energy using both Biochemical and Thermochemical processes. For the rocketry program at Morgan, my team is currently working on developing a Data Acquisition System (DAQ) for the onboard system. I have presented my research works at several international conferences within and outside the USA.