



THE UNIVERSITY OF TEXAS AT EL PASO
INDUSTRIAL, MANUFACTURING & SYSTEMS ENGINEERING

Thank you
TO THIS YEAR SUPPORTING
PARTNERS AND PRESENTERS

IMSE DAY
SMART MANUFACTURING
SUMMIT 2021



THE UNIVERSITY OF TEXAS AT EL PASO
College of Engineering,
Industrial, Manufacturing & Systems Engineering,
500 West University Avenue
El Paso, Texas 79968
(915) 747-5752
imse.utep.edu



EL PASO NATURAL GAS CONFERENCE CENTER
NOVEMBER 17, 2021
8:30 AM TO 5:00 PM
Open to all students and faculty



WELCOME TO THE SMART MANUFACTURING SUMMIT, CELEBRATING IMSE DAY AT UTEP

I am very pleased to welcome you to the 2021 Smart Manufacturing Summit hosted by the Industrial, Manufacturing and Systems Engineering (IMSE) department at The University of Texas at El Paso (UTEP). The purpose of this summit is to address the technical and workforce skills gap regarding Smart Manufacturing (SM) technologies and processes, especially within underserved small and medium manufacturers (SMMs) in the Paso del Norte region. For effective SM technology adoption and implementation to sustain our regional manufacturing advantage, increasing representation of minority workforce demographics with

advanced manufacturing technologies skills is very important.

Our vision is to create a research and education laboratory at UTEP that emphasizes SM technologies and will enable us to educate students within the Paso del Norte region in advanced manufacturing and upskill employees of local SMMs. The summit is part of our broader initiative to create a SM curriculum and certificate program to promote SM concepts and develop industry-related training materials and research laboratory practices. The SM Summit is valuable for our students who get an opportunity to acquire relevant knowledge from industry leaders.

On behalf of the IMSE department and TMAC Paso del Norte, I would like to thank all the speakers and presenters for making the effort to provide their valuable input at the summit, and to all participants for making this summit a great success.

Dr. Amit Joe Lopes

Assistant Professor, IMSE
Regional Director- TMAC Paso del Norte

IMSE DAY | SMART MANUFACTURING SUMMIT 2021

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MESSAGE FROM IMSE DEPARTMENT CHAIR

Welcome to the Industrial, Manufacturing, and Systems Engineering [IMSE] Day Smart Manufacturing Summit 2021

It is an honor to host our annual IMSE Day event after the emergence of the COVID-19 pandemic in 2020. During this event, industry leaders and subject-matter expert panelists will provide their valuable insights on Smart Manufacturing (SM) technologies, digital engineering, enforcement of sustainable automation, and active collaborations needed among industry leaders, researchers from academia, and workforce development institutes, for broader SM adoption. With the continuous growth and advancement in SM technologies, many applications are being enabled in various fields such as healthcare, transportation, surveillance, military, and first responders.

The manufacturing industry has seen a lot of advancement over the years, and this calls for even more innovation and development in Smart Manufacturing technologies. Our academic work here at UTEP emphasizes experiential learning for students from El Paso-Cd. Juarez region. Events, like the annual IMSE Day give students an opportunity to develop leadership and networking abilities, which will be critical in their future careers.

On behalf of the IMSE Department, I want to thank all the speakers and presenters and most importantly, all the students and staff who have participated in making this annual event a success. I encourage all the student community and those attending this event to see this as a networking opportunity and build professional relationships which will enhance your personal, networking, and professional growth. I invite you to also send us your valuable suggestions and feedback on the event to help us organize a better event in the future. I wish you all the best in your learning and future careers.

Dr. Tzu-Liang (Bill) Tseng

CHAIR- DEPARTMENT OF INDUSTRIAL, MANUFACTURING & SYSTEMS ENGINEERING (IMSE)
DIRECTOR- RESEARCH INSTITUTE OF MANUFACTURING AND ENGINEERING SYSTEMS (RIMES)

OUR DEPARTMENT GENERAL OVERVIEW

The Department of Industrial, Manufacturing and Systems Engineering (IMSE) strives to graduate industrial, manufacturing and systems engineers of the highest quality and to conduct state-of-the-art research from an end-to-end enterprise point of view.

Industrial engineering is a unique engineering discipline that integrates the quantitative engineering approach with qualitative insights of human behavior. Industrial and Systems Engineering is vital to providing solutions to complex problems in wide-ranging fields including manufacturing, transportation, technology, healthcare, agriculture, aerospace, and supply chain management. The department's research goes beyond the traditional industrial engineering discipline to solve pressing societal issues. The department is proud to provide students with the flexibility to pursue research across different fields.

The IMSE Department offers a Bachelor's degree in Industrial & Systems Engineering (ISE) and three MS programs in: Industrial Engineering, Manufacturing Engineering, and Systems Engineering. The MS in Systems Engineering is also offered online.



MISSION

- To make a high quality, relevant engineering education available to all residents of the Paso del Norte bi-national region.
- To provide students with a set of skills, knowledge, and attitudes that will permit them to succeed and thrive as engineers and leaders.
- To prepare its graduates to pursue life-long learning, serve the profession and meet intellectual, ethical and career challenges.
- To maintain vital, state-of-the-art research to provide its students and faculty with opportunities to create, interpret, apply and disseminate knowledge for the end-to-end enterprise.



CENTERS AND ACTIVE RESEARCH LABS ASSOCIATED WITH THE DEPARTMENT

RESEARCH INSTITUTE FOR MANUFACTURING & ENGINEERING SYSTEMS (RIMES) - RIMES was created in 1995 as the Institute for Manufacturing and Materials Management (IM3). We have recently renamed the Institute while maintaining its focus on Manufacturing and Materials Management. The institute has also evolved and taken the lead in focusing on the research of new knowledge of systems and its applications to Manufacturing and Engineering Systems. As part of The University of Texas at El Paso, the Institute is committed to education. Members of the RIMES teach classes, sponsor research at the University, and are encouraged to participate in seminars, conferences and lectures. The institute has a long history of collaboration with private industry. We are committed to continue and expand this synergy.

TEXAS MANUFACTURING ASSISTANCE CENTER (TMAC) - TMAC's mission is to increase the global competitiveness of the Texas economy by working to grow the extended manufacturing enterprise. TMAC works with you to make your company more efficient, whether it is energy efficiency, quality issues, or supply chain, we will give you the customized solutions to have the competitive edge, discover financial opportunities and grow your business.

PROGRAM COMMITTEE

BILL TSENG, PH.D.
IMSE CHAIR | RIMES
DIRECTOR



AMIT J LOPES, PH.D.
IMSE ASSISTANT PROFESSOR
TMAC PASO DEL NORTE
REGIONAL DIRECTOR



SREENATH MADATHIL, PH.D.
IMSE ASSISTANT
PROFESSOR



MD FASHIAR RAHMAN, PH.D.
ASSISTANT PROFESSOR OF
RESEARCH



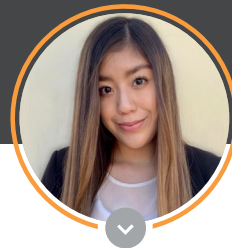
ANAIS ACOSTA
BRANDING MANAGER,
COLLEGE OF ENGINEERING



JOSE LUIS ALANIS MOLINA, MBA, SSBB
IMSE PROGRAM MANAGER



CARMEN ALMERAZ
GRADUATE STUDENT



JESUS A GUTIERREZ ARAIZA
ALPHA PI MU (APM)
HONOR SOCIETY,
PRESIDENT



XU HONGLUN
COMPUTATIONAL SCIENCE
DOCTORAL STUDENT



AL MARTINEZ
WEBMASTER, COLLEGE OF
ENGINEERING



ENRIQUE MARTINEZ
UTEP STUDENT SISE
CHAPTER, PRESIDENT



COLLEGE OF ENGINEERING INDUSTRIAL, MANUFACTURING & SYSTEMS ENGINEERING



389
STUDENT ENROLLMENT



104
TOTAL DEGREES CONFERRED



11
FACULTY

FALL 2020

DEGREES CONFERRED AY 2019-20

(FALL 19, SP20 & SU 20)

Bachelor of Science (B.S.)	73
Industrial & Systems Engineering	73
Master of Science (M.S.)	31
Industrial Engineering	6
Manufacturing Engineering	4
Systems Engineering	21

STUDENT BODY PROFILE - DEGREES CONFERRED AY 2019-20

Ethnicity (UG)	73
Hispanic	43.8%
Mexican International	15.1%
Other International	41.1%
Gender (UG)	
Female = 21% Male = 79%	
Ethnicity (MS)	31
Hispanic	58.1%
Mexican International	22.6%
Unknown	6.5%
White Non-Hispanic	12.9%
Gender (MS)	
Female = 35% Male = 65%	

FALL 2020 ENROLLMENT

Undergraduate	228
Industrial & Systems Engineering	208
Lower Division Industrial Engineering	20
Master's	*161
Industrial Engineering	31
Manufacturing Engineering	23
Systems Engineering	94
Systems Engineering – AT&T	13

*These numbers do not include certificates, only actual degrees.

STUDENT BODY PROFILE - FALL 2020 ENROLLMENT

Ethnicity (UG)	228
Asian American	0.4%
Black Non-Hispanic	0.9%
Hispanic	64%
Mexican International	10.5%
Other International	21.1%
Two or more races	0.4%
Unknown	1.3%
White Non-Hispanic	1.3%
Gender (UG)	
Female = 34% Male = 66%	
Ethnicity (MS)	161
Black Non-Hispanic	6.2%
Hispanic	60.2%
Mexican International	19.9%
Native Hawaiian or Other Pacific Islander	0.6%
Other International	1.2%
Unknown	1.2%
White Non-Hispanic	10.6%
Gender (MS)	
Female = 30% Male = 70%	

FACULTY AS OF FALL 2020

Total	11
Tenured	5
Tenure-track	3
Non-Tenure track	3
Faculty Rank (T/TT)	
Assistant	3
Associate	4
Professor	1
Faculty Rank (Non-Tenure Track Faculty)	
Research Assistant Professor	3
Gender (T/TT Faculty)	
Female	1
Male	7
Gender (Non-Tenure Track Faculty)	
Female	1
Male	2

PROGRAM AGENDA

IMSE DAY SMART MANUFACTURING SUMMIT 2021

8:30AM - 9:00AM | COFFEE AND REGISTRATION

9:00AM - 9:05AM | OPENING REMARKS: PATRICIA NAVA, PH.D., PE
College of Engineering Interim Dean | Electrical and Computer Engineering Professor, and
El Paso Electric Company Professor in Education Research
The University of Texas at El Paso

9:10AM - 9:55AM | CHRISTOPHER COLAW
Fellow, Quality & Mission Success, **Lockheed Martin Corporation**
DISCUSSION TOPIC: Preparing for A.I with Lessons from your Gage R&R Past

10:00AM - 10:45PM | ERIC SHERRILL
National Sales Director, **Toolkit Technologies**
DISCUSSION TOPIC: Industry 4.0 Demonstration

11:00AM - 11:45AM | LEILA MELENDEZ
CEO, **Workforce Solutions Borderplex**
DISCUSSION TOPIC: The Middle-Skill Gap

12:00PM - 1:00PM | LUNCH / POSTER SESSION

1:15PM - 2:00PM | CONRAD LEIVA
VP of Ecosystem and Workforce Development, **CESMII:**
The Smart Manufacturing Institute
DISCUSSION TOPIC: How IT-OT Convergence is Changing the Skills Required for
Smart Manufacturing Jobs

2:15PM - 3:00PM | SREENATH CHALIL MADATHIL, PH.D.
IMSE Assistant Professor, **The University of Texas at El Paso**
DISCUSSION TOPIC: Challenges in Digital Twin Adoption among Small and
Medium Enterprises

3:10PM - 3:55PM | SMART MANUFACTURING TECHNOLOGY FORUM
NATALIE LITTLEFIELD, JD, Vice President of Strategy
The Borderplex Alliance

DIANA OLIVAR, Managing Director and CEO
Boost Human, LLC

JAVIER ACOSTA, Founder
Mechatronics Automation USA & MX
DISCUSSION TOPIC: Industry 4.0 - Building Resilience with Automation,
Artificial Intelligence & Trust

MO ABUALI, PH.D., CEO and Managing Partner
IOT Co
DISCUSSION TOPIC: Zero-Downtime and Zero-Defect Manufacturing,
Leveraging Industry 4.0.

4:00PM - 4:45PM | SHAWN S. SMITH, PH.D., PMP
IMSE Lecturer, **The University of Texas at El Paso**
Senior Systems Engineer / Business Development, **Alpha Omega Group**
DISCUSSION TOPIC: Cybersecurity and the Need for Cyber Systems Engineering

4:50PM - 5:00PM | CLOSING REMARKS: BILL TSENG, PH.D., CMFGE
IMSE Chair & Professor, **The University of Texas at El Paso**



CHRISTOPHER L. COLAW

Fellow, Quality & Mission Success
Lockheed Martin Corporation

Chris has recently been selected as one of the “Top 100 Visionaries in Education” by the Global Forum for Education and Learning for his contributions to development of global university talent.

PREPARING FOR A.I WITH LESSONS FROM YOUR GAGE R&R PAST

Adoption of Artificial Intelligence [AI] is a critical first step for the Quality 4.0 Organization. After the declaration of support for AI is made, the organization must begin to focus on how to qualify and incorporate AI in a way that is consistent with expectations from customers and the 3rd Party Registrars. From a gage qualification and policy perspective, this expectation is historically based on traditional (non-AI) gages and metrology and a focus on calibration and Gage R&R. AI solutions designed to make conformity decisions require the creation of an adapted expectation set, which is greatly influenced by these legacy practices. When utilizing AI, there is hardware and software involved, but not the same as organizations are used to dealing with. The hardware is essentially a visual camera, not a measurement device. Given this, one may ask, what do I calibrate and what is the measurement variation that I must control? AI maturity depends on detection and classification capabilities, as well as an adequate source of training data, in addition to minimized hardware variation (visual cameras and lighting hardware).

Christopher “Chris” Colaw is a Lockheed Martin Fellow with expertise in digital transformation, inspection technology, automation, and 3D modeling. Additionally,



ERIC WILLIAM SHERRILL

National Sales Director
Toolkit Technologies

INDUSTRY 4.0.

Through the lens of education, topics such as, but not limited to digitalization and digital twins, cybersecurity, smart sensors, and the evolution of the ‘smart factory’ as it relates to industrial automation and manufacturing can prepare students, schools, and communities for nowadays engineering challenges across interdisciplinary operating environments.

Eric Sherril is a seasoned Education Solutions Provider with a diverse background ranging from corporate management positions, sales executive positions, entrepreneurial ventures, hospitality management roles, and volunteer experiences. Furthermore, Eric earned his Bachelor of Commerce (BCom) from the University of British Columbia Specialization in Finance with Concentration in International Business from Sauder School of Business. He currently holds a National Sales Director position in Toolkit Technologies, where industry-proven training solutions are provided whereas empowering the next-generation of workforce in areas such as Robotics, Industry 4.0, Mechatronics, Electrical Trades, process control and instrumentation, amongst others.

THE MIDDLE-SKILL GAP

70% of the workforce in El Paso is in positions that are in the bottom half of jobs per the wages they earn. Most positions are in entry-level jobs. To increase the productivity levels of the companies in the region and attract larger companies, we must enhance the skills of the workforce. WSB will describe how the region’s workforce is ready to advance into middle and high-skill occupations to strengthen the supply chain and become a more growth-ready economy.

Leila Melendez is CEO of Workforce Solutions Borderplex which serves the six counties in Far West Texas. Leila has been with WSB for over six years and began her role on the first day El Paso recorded its first COVID-19 case. Her time as CEO has been leading her workforce development board through a leadership change and an unprecedented economic disruption. Her leadership has helped WSB be steady and responsive during the crisis, and strategic and visionary as it looks ahead towards economic re-development.

Leila was born, raised, and educated in El Paso, having received her master’s degree from The University of Texas at El Paso. She is an active member of her community and participates in several civic and professional organizations.



LEILA MELENDEZ

Chief Executive Officer
Workforce Solutions Borderplex



CONRAD LEIVA

VP of Ecosystem and Workforce Development
CESMII: The Smart Manufacturing Institute

manufacturing.

Conrad has over 20 years of experience in manufacturing systems development and implementation and holds an M.S. in Industrial Engineering from the Georgia Institute of Technology.

He is a lifetime member and contributor of MESA International and a frequent speaker at conferences and his writing includes guidebooks, whitepapers, online courses and articles on Smart Manufacturing, Industrial Internet of Things (IIoT), Digital Thread, Lean, MES, MRO, quality management, regulatory compliance, and ROI analysis.

HOW IT-OT CONVERGENCE IS CHANGING THE SKILLS REQUIRED FOR SMART MANUFACTURING JOBS

Operational Technology (OT) and Information Technology (IT) have had a long history of isolation from each other in many industrial organizations. However, they have been slowly converging on the scene as companies make advances towards Smart Manufacturing methods.

In this presentation, we will discuss how these technology areas have been converging over the last few decades and how it has been changing the workforce skills needed to support manufacturers implementing Smart Manufacturing methodologies to remain competitive in today’s highly digitally connected manufacturing ecosystem.

Conrad Leiva is VP of Ecosystem and Workforce Development at CESMII – the Smart Manufacturing Institute (<https://www.cesmii.org/>). In his role, Conrad is accelerating manufacturing innovation and Smart Manufacturing adoption through a knowledge-building ecosystem of regional centers, technology partners, and academic institutions. As recognized industry authority, he engages manufacturing business leaders, solution providers, educators and practitioners across all dimensions of industry to develop and share knowledge on both How and Why to leverage information technology in



SREENATH CHALIL MADATHIL, PH.D.

IMSE Assistant Professor,
The University of Texas at El Paso

CHALLENGES IN DIGITAL TWIN ADOPTION AMONG SMALL AND MEDIUM ENTERPRISES

Supply shortages from several second-tier and third-tier suppliers combined with demand volatility caused by the COVID-19 pandemic wreaked havoc on several businesses, manufacturers, and suppliers by impacting the existing supply chain networks. This pandemic has exposed several unpleasant and complicated conditions such as our lack of preparedness during supply disruptions, inability to find alternate sourcing mechanisms, ignorance of efficient pivoting strategies, inadequate data on a local region’s capabilities to help struggling businesses, and lack of awareness among small and medium enterprises on new more innovative technologies such as digital twin, blockchain, and intelligent and connected manufacturing.

These new technologies are part of the backbone of the Industry 4.0 initiative to digitize manufacturing. Several SME and businesses could have made informed decisions and efficiently pivoted during the pandemic if they used Industry 4.0 technologies such as smart manufacturing, Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IIoT), cybersecurity, and digital twins (DT) and were aware of various uncertainties’ impacts. Data-driven analysis of complex interconnected supply chains creates a competitive advantage for companies to evaluate trade-offs in capacity, service, inventory, and total landed costs. A digital twin, a computerized visualization model, can

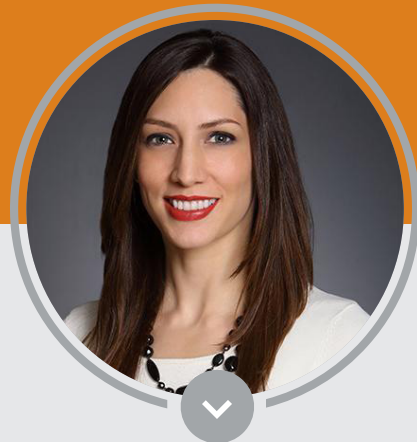
replicate the supply chains’ fundamental intricacies in their number of product types, warehouses, supplier levels, customers, logistics, and inventory, and can realize significant benefits for the manufacturing industry, especially for small and medium enterprises (SMEs). Artificial Intelligence (AI) integrated digital twin technology can augment decision-making by carefully incorporating insights from a machine learning environment with a powerful and versatile virtual environment that can simulate many system behaviors. In this talk, I present some challenges of adopting Digital Twins by small and medium enterprise.

Dr. Sreenath Chalil Madathil has extensive research background in operations research, data analysis, simulation, and process improvement in healthcare, energy, and supply chain management. Dr. Chalil Madathil earned his doctoral degree in industrial engineering from Clemson University. He comes to UTEP from the Watson Institute of Systems Excellence (WISE), a SUNY Research Foundation at Binghamton University. His research interest focuses on using computer simulation models for improved decision making. Dr. Chalil Madathil has publications in various top peer reviewed journals such as Computers and Industrial Engineering, Applied Soft Computing, Expert Systems with Applications, and Production & Manufacturing Research.

SMART MANUFACTURING TECHNOLOGY FORUM

PANELIST

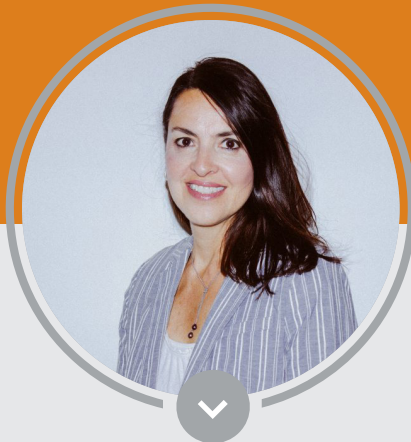
NATALIE LITTLEFIELD, JD
Vice President of Strategy
The Borderplex Alliance



Natalie Littlefield is Vice President of Strategy at The Borderplex Alliance where she developed and wrote the 2025 regional economic development strategic plan and is currently building several new industry associations and committees and working with partners to implement the strategic plan.

Prior to this role, Natalie oversaw the administration of several workforce development programs. She is on the Board of Directors at the El Paso Chamber, an advisory board member for UTEP's School of Industrial, Manufacturing and Systems Engineering (IMSE) as well as for UTEP's College of Education; she is a member of the Communications Council for the El Paso Collaborative for Academic Excellence (EPCAE), a steering committee member for Region 19's CTE Pay for Success Program in support of the biomedical industry, and a member of the ASPIRE Industry and Innovation Board. She is a member of Progress321 and the International Economic Development Council.

DIANA OLIVAR
Managing Director and Chief Executive Officer
Boost Human, LLC



Diana Olivar is the Managing Director and CEO of Boost Human, LLC a software development company headquartered in El Paso, Texas. Boost Human leverages VR/AR to consult and develop custom software which focuses on bridging the transformation from traditional modalities of learning into immersive and experiential learning. The outcomes are increased productivity with learning that is deeper, faster, and retained longer accelerating knowledge transfer. We partner with innovative companies like IoTco to provide the latest Industrial Internet of Things (IIoT) via Predictive and Analytics software to our region. Diana is an equity investor and is focused on business development for Diamond Crest Capital.

Prior to returning to El Paso Diana spent 20 years in Chicago working in various sales roles in the telecommunications and hardware & software industries. She earned a degree in Economics from the University of Illinois in Chicago.

Diana is very passionate about her community and has volunteered many hours to causes near and dear to her heart such as the Humane Society, Chicago Park District, Child Protective Services (CPS) and is always willing to help mentor young minds in discovering financial literacy.

JAVIER ACOSTA
Founder
Mechatronics Automation USA & MX



INDUSTRY 4.0 - BUILDING RESILIENCE WITH AUTOMATION, ARTIFICIAL INTELLIGENCE & TRUST

Industry 4.0, Intelligent Automation, Robotic Platforms, Artificial Intelligence applied on Industry and Industrial Automation.

Born in Cd. Juárez México, and father of three beautiful children, Javier is an electromechanical engineer, and inventor with expertise across the following knowledge areas: traceability 4.0, face biométrica, TEA, Sonni Robotics and IDM.

Javier is also the Founder of The Family of the Future, a socially responsible program offering scholarships to children of limited economic resources in high crime neighborhoods in Juárez México and teaching technology to empower them to build their future. Furthermore, Javier has also participated in TEDx as a speaker; and be present on ad hoc events such as: México Auto Industrial Summit 2019-2021, Instituto Politécnico Nacional (IPN) de México, and Bio El Paso-Juárez Summit, UTEP, UACJ, ITCJ & Tecnológico de Monterrey.

MO ABUALI, PH.D.
CEO and Managing Partner
IOT Co



ZERO-DOWNTIME AND ZERO-DEFECT MANUFACTURING, LEVERAGING INDUSTRY 4.0

Act now, demonstrate leadership, build the business case for Industry 4.0 and Predictive Analytics, and get started. Data first! Digitalization is from the past; predictive analytics and artificial intelligence is the future. Industry 4.0 is all about process, technology, and people. Empower your maintenance and quality personnel with predictive and prescriptive insights. A Systematic Approach to "Think Big, Start Small, and Win ROI with AI"

Dr. Mo Abuali is the CEO and Managing Partner at IoTco, the internet of things company. He is a strategic and transformative technology and business management leader with 20-year record of achievement driving and sustaining change in Manufacturing. Mo serves Industrial and Manufacturing Clients in Automotive, Aerospace & Defense, and others, providing Digital Transformation, Industrial IoT (IIoT), and Predictive Analytics technology and services, as well as the IoT Academy for Industry 4.0 Training. Mo has a doctorate degree in Industrial Engineering and has worked with companies like IBM, P&G, Omron, and Toyota.

SEMINARS & PRESENTERS



SHAWN SMITH, PH.D.

Lecturer and Senior Systems Engineer
The University of Texas at El Paso

Director of Business Development
Alpha Omega Group

CYBERSECURITY AND THE NEED FOR CYBER SYSTEMS ENGINEERING

This briefing will cover the NIST Cybersecurity Framework, including introducing the Framework Core, Implementation Tiers, and Framework Profiles. It will also cover NIST Special Publication 800-53 r5 Risk Management Framework. Together, these two documents form the basis for the NIST cyber risk management ecosystem which enables organizations to manage cyber risk using the frameworks five function Identify, Project, Detect, Respond, and Recover process.

Cybersecurity is a wicked problem. It is persistent, dating to the 1960's (and perhaps as early as the 1950's) when bad actors would find ways to steal (use for free) the federally regulated long distance telephone service provided by AT&T (Brush, 2014).

On May 12th, 2021 Executive Order 14028 was issued by President Joe Biden who indicated "The United States faces persistent and increasingly sophisticated malicious cyber campaigns that threaten the public sector, the private sector, and ultimately the American people's security and privacy" (Improving the Nation's Cybersecurity, 2021).

Cybersecurity is broad scoped; statistics from the U. S. Federal Bureau of Investigation Internet Crime Complaint Center (IC3) for the year 2020 reveal that nearly 792K complaints were reported, an increase of more than 69% from 2019 with an estimated cost of \$4.1B (Federal Bureau of Investigation (FBI), 2021). Cybersecurity is complex and

interlinked; we find new attacks on individuals, companies, and governments daily. And there is uncertainty about the efficacy of technical, policy, and legal actions taken (Cabrera & Cabrera, 2015). Finally, the mass migration to remote, technology-enabled work and commerce created by the Covid-19 Pandemic in 2020-21 added additional complexity and urgency to securing these online systems vital to individuals, business, industry, and government.

Dr. Shawn S Smith is a Senior Systems Engineer and Director of Business Development at Alpha Omega Group, a small, highly specialized firm delivering engineering and program management services to Navy and Air Force clients. Smith serves UTEP as a Lecturer in the College of Engineering, teaching SE5341 and is a member of the Industrial, Manufacturing, and Systems Engineering Advisory Board. Over a 40-year career in business and industry, he has held technical and management positions at firms including Texas Instruments, ADC Telecommunications, and Booz Allen Hamilton including Facilities Engineer, Telecommunications Manager, Senior System Engineer Product Manager, and Product Manager/Director of Technology.

He lives in Oceanside CA and when not spending time with his five grandchildren, he runs, hikes, kayaks, and reads.

ARTIFICIAL INTELLIGENCE APPLIED RESEARCH

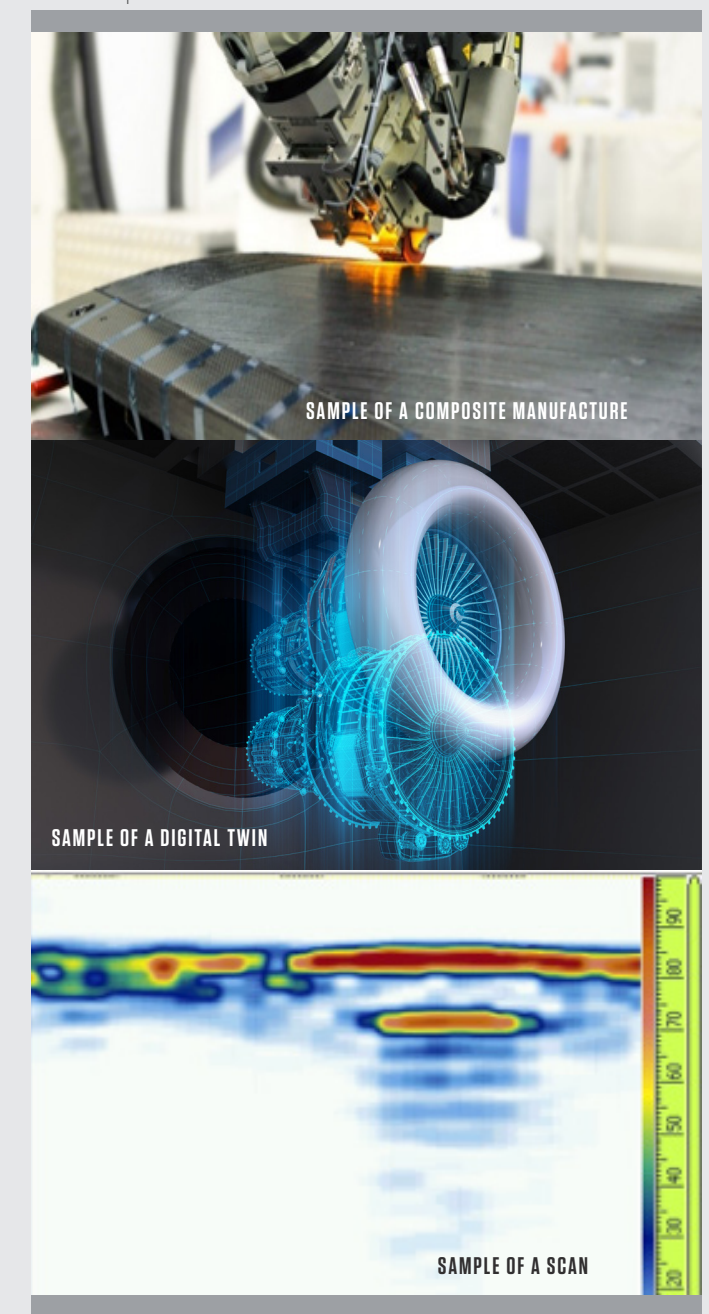
NON-DESTRUCTIVE EVALUATION AND DIGITAL TWIN PROJECT

Lockheed Martin has awarded funding for a project with the Department of Industrial, Manufacturing and Systems Engineering [IMSE] at The University of Texas at El Paso for research on Non-Destructive Evaluations (NDE) of different material composites. Present day, Non-Destructive evaluations start by scanning a composite plaque with an ultrasound scanner which produces ultrasound readings of the material. The produced readings are then evaluated by a specialist (i.e., a materials expert) to determine several qualities of the composite material, for example if the material is damaged and if so, what kind of damage exists. With the proposed project Lockheed Martin and the IMSE will investigate the possibility of automatically providing the same quality of inspection results as in a human-driven evaluation by applying the latest Deep Learning algorithms to perform defect detection on the ultrasound scans. The project will also elaborate on the possibility of using the extracted data to create a so called 'Digital Twin', or a recreation of the material composite in a digital space.

Furthermore, this project will integrate results from Non-Destructive Evaluations and Digital Twin recreations to the 'cutting-edge' quality-control framework called Quality Information Framework (QIF). With QIF the project will formalize the results obtained from Non-Destructive Evaluations driven by Deep Learning detection into a format that will allow specialists to obtain a 'complete picture' of the status of a composite material. For example, an analyst can have access to who and when the composite was produced, or which are the specifications of the composite, as well as a rendering of the composite. With the capabilities offered by Deep-Learning driven NDE and the integration with the Quality Inspection Framework this project will generation a world-class level product that will speed up the evaluation of materials at an industrial scale.

The Non-Destructive Evaluation and Digital Twin project currently employs a group of five Research Assistants led by Dr. Bill Tseng. The team consists of multiple departments including, Department of Computer Science, Mechanical Engineering, and Industrial, Manufacturing, and Systems Engineering. By participating in this project, Research Assistants will face challenges that will test their knowledge in their own area of expertise, expose them to a real-world collaboration environment, and most importantly expose them to other areas of expertise other than their own. By the time of completion of this project, students would have gone through Phase 1 and Phase 2 of development of the project.

The project will embark on a third phase at the beginning of the first semester of 2022. During Phase 3, it is expected that the scope of project will increase in terms of what Deep Learning should be able to detect, what QIF should report, and in the kinds of composite manufacturing samples the project team can produce.



DIGITAL TWIN

APPLIED RESEARCH

DIGITAL TWIN FOR SUPPLY CHAIN MANAGEMENT

The small and medium enterprises (SMEs) are critical to create more opportunities in the USA and a cost-effective supply chain management (SCM) is crucial for their survival and growth. As Industry 4.0 is happening now, it is a promising change for supply chains to adapt to the toolkits such as Internet of things (IoT), cloud computing, digital twins, cyber-physical systems, and artificial intelligence. Industry 4.0, an amalgam between physical and digital systems, creates a synergistic cyber-physical ecosystem that enables optimization, customization, productivity, and safety improvement.

Digital Twin is a novel concept that utilizes the vast amounts of data generated in a connected manufacturing enterprise to create a virtual model of the manufacturing enterprise. A digital twin, a computerized visualization model, can replicate the supply chains' fundamental intricacies in their number of product types, warehouses, supplier levels, customers, logistics, and inventory, and can realize significant benefits for the manufacturing industry, especially for small and medium enterprises (SMEs), by enabling virtual data analysis of key parameters within the entire manufacturing supply chain, and providing actionable insights on future operations. In addition, they provide a macroscopic view of the organizations' supply chains to identify uncertainties, potential volatilities, and opportunities to optimize. Moreover, the current supply

chain visualization using these advanced digital twin models can help regional economic development (ED) organizations and cities' ED and planning departments advance various regional economic development strategic plans to foster their regional supply chain capabilities.

Supply shortages from several second-tier and third-tier suppliers combined with demand volatility caused by the COVID-19 pandemic wreaked havoc on several businesses, manufacturers, and suppliers by impacting the existing supply chain networks.

This pandemic has exposed several unpleasant and complicated conditions such as our lack of preparedness during supply disruptions, inability to find alternate sourcing mechanisms, ignorance of efficient pivoting strategies, inadequate data on a local region's capabilities to help struggling businesses, and lack of awareness among small and medium enterprises on new more innovative technologies such as digital twin, blockchain, and intelligent and connected manufacturing. In the Industry 4.0 "utopia," there would have existed systems where all manufacturers and their supply chain are fully compliant with Industry 4.0 technologies with interconnected systems that communicate with each other through a manufacturing data exchange and make autonomous decisions for overall efficiency improvement as illustrated in Figure 1.

Data-driven analysis of complex interconnected supply chains creates a competitive advantage for companies to evaluate trade-offs in capacity, service, inventory, and total landed costs. However, according to the report on middle-market manufacturer's roadmap to Industry 4.0, the adoption of these digitization revolutions of cutting-edge technologies seems aspirational for many of small and medium enterprises (SME).

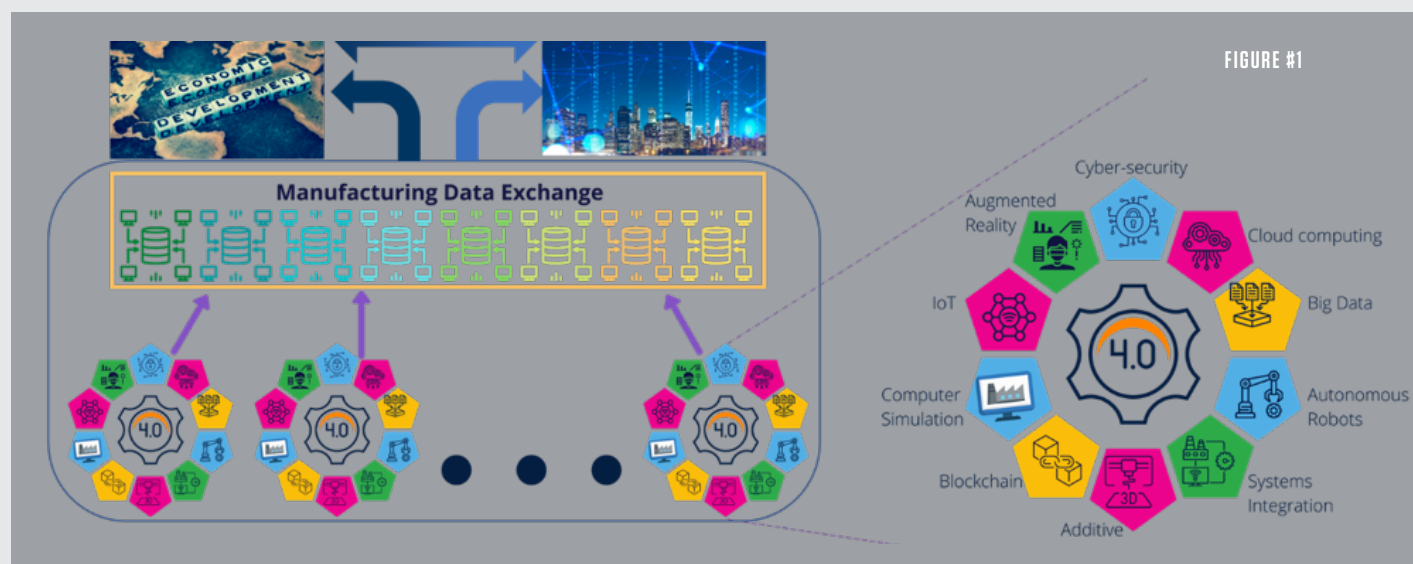
Uncertainty on the return-on-investment, lack of trust in cyber-physical systems and data sharing, cyber-security issues, and lack of talent are some of the attributes that caused many SMEs to slow down the adoption of Industry 4.0 technologies. Moreover, the COVID-19 pandemic has pushed SMEs to develop resiliency strategies to manage their supply chains' inherent risks. They must continuously respond to changing demand patterns and supply issues and had to find a balance between industry 4.0 technologies' adoption and maintain their current operations. Consequently, the SMEs became reluctant to embrace and implement Industry 4.0 technologies. They became skeptical if pivoting their traditional operational systems could be efficiently expanded to support the new framework.

When the Industry 4.0 technological framework offers data abundance, a digital twin is decisive for efficient asset lifecycle management. Digital Twins acquire process data and product data through accessing a secure portal within Industry 4.0 technologies. These comprehensive modeling and simulation tools, capable of generating a digital replica of the systems, create near-real-time system models. In addition, digital twin modeling helps organizations virtually simulate their manufacturing systems, study various outcomes due to several system uncertainties, perform several what-if scenarios, and provide alternatives for the optimal operating environment of an enterprise.

Digital Twin consists of the physical asset, virtual asset, and interaction (data transmitted from the physical asset to the virtual asset). Digital Twin can also utilize AI and IoT that transmit data via sensors or other devices capable of transmitting real-time data from the physical asset to the virtual asset, creating data (Big Data).

These new technologies are part of the backbone of the Industry 4.0 initiative to digitize manufacturing. The information exchange among this cyber-physical system requires an interconnected high-performance computing system capable of doing advanced AI and ML in real-time. Analysis of this data

helps get feedback, prevent breakdowns, simulate real-case scenarios in a virtual environment with the data provided by the physical environment, simulate uncertain environments, and observe the performance of the physical assets. Several businesses could have made informed decisions and efficiently pivoted during the pandemic if they used such technologies and were aware of various uncertainties' impacts. Moreover, organizations that adopted Industry 4.0 technologies have shown increased productivity, revenues, and profitability.



COMPILATION OF POSTERS

BRIEFINGS WITH RESEARCH INFORMATION

DIMENSIONAL ACCURACY PREDICTION FOR SHAPE MEMORY POLYMER USING ANNs



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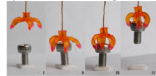
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Research/Project Objective

- To predict dimensional accuracy for shape memory polymer (SMP)
 - To fabricate SMP/Graphene-Oxide (GO) nanocomposites using projection stereolithography (SL)
 - To develop artificial neural networks (ANN) as modelling tool for 3D printing

Background

- Shape-memory polymers (SMPs) are polymeric smart materials that have the ability to return from a deformed state (temporary shape) to their original (permanent) shape when induced by an external stimulus (trigger) [1], such as temperature change.
 - Soft gripping in robotics
 - Sport wears
 - Self-adjusting wires
 - Self-repairing structures
 - Medical application (implants)
- Because of their potential application as soft active materials, SMPs and its fabrication process has recently attracted much attention [2].



Research Methodology: Part Fabrication

- SMP photo-resin results from mixing of tert-butyl acrylate (tBA) as monomer solvent, diethylene glycol diacrylate (DEGDA) as crosslinker, and Phenylbis (2,4,6-trimethylbenzoyl) phosphine oxide (BAPO) as photo-initiator
- This SMP resin was selected because it is suitable for digital light projector (DLP) process.
- Graphene Oxide (GO) nanoflakes were chosen as photo-thermal nanofiller due to their high photo-thermal properties over other materials
- SMP resin (tBA/ DEGDA/ BAPO) was fabricated by using DEGDA content of 20 wt.%, BAPO content constant (2 wt.%), and mixing (Vortex Mixer) for 30 min

Research Methodology: Part Fabrication

- Uniform and continuous SMP/GO nanocomposites with graphene-oxide content (2wt.%) were obtained by blending with SMP resin and GO were mixed (Vortex Mixer) for 30 min
- Homogeneous pure SMP and SMP/GO were poured onto a DLP bath for 3D part fabrication
- The DLP printer (Wanhao duplicator 7) was used in this process

Parameter	Value
Slit thickness (mm)	0.025
Exposure Time (min)	3000
Bottom Exposure (min)	6000
# of Bottom Layers	2

Research Methodology: Accuracy Prediction

- Clearly, the dimensional variations are observed on the produced samples which is one of the main challenges in producing SMPs
- ANN modelling designs were implemented using stereolithography (SL) historical data with 140 data points

- Layer thickness (mm) - displacement of platform on Z axis
- Curing depth (s) - light penetration during curing
- Hatch spacing (mm) - distance between projected curing light beams



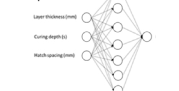
Research Methodology: Accuracy Prediction

We designed two neural networks [3] for experiment

- 3 inputs
- 3 hidden layers/4 neurons each
- 1 output



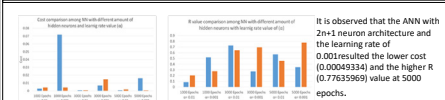
- 3 inputs
- 1 hidden layers with 2n+1 neurons
- 1 output



Experimental Setup

- 140 data points
 - 111 data samples for training
 - 29 samples for testing
- Three different number of epochs
 - 1000 epochs, 3000 epochs, and 5000 epochs
 - 0.01 and 0.001 learning rate
- Performance is evaluated based in
 - Cost convergence and
 - Pearson correlation (R) coefficient for dimensional error response

Result and discussion



It is observed that the ANN with 2n+1 neuron architecture and the learning rate of 0.001 resulted the lower cost (0.00049334) and the higher R (0.77625965) value at 5000 epochs.

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Acknowledgements

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A SEQUENTIAL BAYESIAN PARTITIONING APPROACH FOR ONLINE STEADY-STATE DETECTION OF MULTIVARIATE SYSTEMS



A Sequential Bayesian Partitioning Approach for Online Steady-State Detection of Multivariate Systems

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Research/Project Objective

- An efficient online steady-state detection method for multivariate systems**
 - A Bayesian piecewise constant mean and covariance model
 - A recursive updating method is developed to calculate the posterior distributions
 - The duration of the current segment is utilized for steady-state testing

Background

- Detecting if a system or a process is steady is a significantly important task in many engineering problems, such as process analysis and optimization, fault detection and diagnosis. In these applications, the steady state is often defined as a state where the mean of the time series stays unchanging [1-2].
- Steady state detection is using various statistical techniques to identify the transition from nonstationary state (also called transient state, start-up or warm-up period) to the steady state.

Sequential Bayesian Partitioning Approach

1. Piecewise Constant Modeling

$$\Phi_t = \begin{cases} \Phi^{(1)}, & \text{if } c_0 < t \leq c_1 \\ \Phi^{(2)}, & \text{if } c_1 < t \leq c_2 \\ \vdots & \vdots \\ \Phi^{(k)}, & \text{if } c_{k-1} < t \leq c_k \\ \Phi^{(k+1)}, & \text{if } c_k < t \leq c_{k+1} \end{cases}$$

where: $\Phi^{(i)}$ is the distribution parameter of the i th segment and $\Phi_t = (\mu_t, \Sigma_t)$.

2. Bayesian Formation and Prior Specification

$$P(\tau_t = j | \tau_{t-1} = j') = \begin{cases} 1 - G(t - j'), & \text{if } j = j' \\ G(t - j') - G(t - 1 - j'), & \text{if } j = j' + 1 \\ 1 - G(t - 1 - j'), & \text{if } j = t \\ 0, & \text{otherwise} \end{cases}$$

where $0 \leq j \leq t-1$, $G(\cdot)$ is the cumulative distribution function for the segmental duration.

3. Sequential Bayesian Partitioning (SBP)

It is essential to calculate the posterior distribution of the segmental duration, or equivalently the latest change-point sequentially [3].

The posterior distribution can be expressed as

$$P(\tau_{t+1} = j | X_{1:t+1}) \propto p(\tau_{t+1} = j, X_{t+1} | X_{1:t})$$

where $j = 0, 1, \dots, t$ is the observation index.

$$P(\tau_{t+1} = j | X_{1:t+1}) = \begin{cases} P(\tau_{t+1} = j, X_{t+1} | X_{1:t}) & j = t \\ P(\tau_{t+1} = j, X_{t+1} | X_{1:t}) & j \leq t-1 \end{cases}$$

$$P(\tau_{t+1} = j | X_{1:t+1}) \propto \begin{cases} (1 - p_0)P(\tau_t = j | X_{1:t})p(X_{t+1} | X_{1:t}, \tau_{t+1} = j), & j = t \\ p_0P(X_{t+1}), & j \leq t-1 \end{cases}$$

$$P_t = P(t - \tau_t \geq L_0 | X_{1:t}) = P(\tau_t \leq t - L_0 | X_{1:t}) = \sum_{l=0}^{t-L_0} P_l(t)$$

$$P_l(t) = \begin{bmatrix} p_0^{(t-L_0+1)} p_0^{(t-L_0+2)} \dots p_0^{(t-L_0+t-1)} \\ p_0^{(t-L_0+1)} p_0^{(t-L_0+2)} \dots p_0^{(t-L_0+t-1)} \\ \vdots \\ p_0^{(t-L_0+1)} p_0^{(t-L_0+2)} \dots p_0^{(t-L_0+t-1)} \end{bmatrix} \begin{bmatrix} (1-p_0)p_{L_0} & 0 & \dots & 0 \\ 0 & (1-p_0)p_{L_0} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & (1-p_0)p_{L_0} \end{bmatrix} \begin{bmatrix} p_0 \cdot P(X_{t-L_0+1}) \\ p_0 \cdot P(X_{t-L_0+2}) \\ \vdots \\ p_0 \cdot P(X_{t-L_0+t-1}) \end{bmatrix}$$

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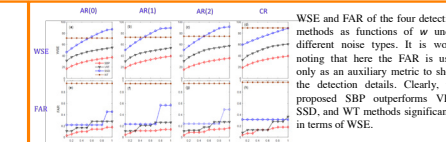
$$P_t = \begin{bmatrix} p_0^{(t-L_0+1)} p_0^{(t-L_0+2)} \dots p_0^{(t-L_0+t-1)} \\ p_0^{(t-L_0+1)} p_0^{(t-L_0+2)} \dots p_0^{(t-L_0+t-1)} \\ \vdots \\ p_0^{(t-L_0+1)} p_0^{(t-L_0+2)} \dots p_0^{(t-L_0+t-1)} \end{bmatrix} \begin{bmatrix} (1-p_0)p_{L_0} & 0 & \dots & 0 \\ 0 & (1-p_0)p_{L_0} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & (1-p_0)p_{L_0} \end{bmatrix} \begin{bmatrix} p_0 \cdot P(X_{t-L_0+1}) \\ p_0 \cdot P(X_{t-L_0+2}) \\ \vdots \\ p_0 \cdot P(X_{t-L_0+t-1}) \end{bmatrix}$$

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WSE and FAR of the four detection methods as functions of w under different noise types. It is worth noting that here the FAR is used only as an auxiliary metric to show the detection details. Clearly, the proposed SBP outperforms VRT, SSD, and WT methods significantly in terms of WSE.

2. Comparison with Other Methods

- SBP method is better than other methods
- The optimal window size of 24 is selected.
- The overall significance level α is set as 0.05. Based on the Sidak inequality, the individual significance level should be 0.0127.

Signal	Noise	R	T _{th}	WSE	FAR	WSE	FAR	WSE	FAR
AR(0)	0.001	27.3	47.8	66.3	78.2	0.00	0.00	0.24	0.01
	0.01	28.1	20.0	65.8	40.3	0.14	0.25	0.55	0.91
	0.1	28.6	25.1	70.1	39.8	0.17	0.69	0.68	0.94
	0.001	27.3	47.8	66.3	78.2	0.00	0.00	0.24	0.01

should be 0.0127:


Overall	37.8	54.4	86.8	71.4	0.18	0.28	0.45	0.45	0.45
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Case Study

COMPILATION OF POSTERS

BRIEFINGS WITH RESEARCH INFORMATION

PREDICTING ZERO-BIN IN THE SEMICONDUCTOR MANUFACTURING INDUSTRY: MACHINE LEARNING ALGORITHMS



Predicting Zero-Bin in the Semiconductor Manufacturing Industry: Machine Learning Algorithms

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Department of Industrial, Manufacturing & Systems Engineering (IMSE)
Research Institute for Manufacturing & Engineering Systems (RIMES)
The University of Texas at El Paso

Research/Project Objective

This research evaluates the effectiveness of machine learning algorithms to identify significant factors contributing to manufacturing part outages (i.e., zero-bin) to keep manufacturing equipment running at total capacity through a case study in the semiconductor industry.

Background

- We are in the middle of an industrial revolution where big data and the 'smart machine' can be used to improve manufacturing throughput.

- Manufacturing unavailability is often due to the lack of critical manufacturing-related spare parts

- Spare parts are assigned characteristics such as Leadtime that aid in categorizing and managing the part's supply chain company wide.

Research Design

1. Partitioning based K-Means clustering proved best due to Euclidean distance measured tied to arbitrary centralized data point not necessarily in the dataset.
2. Selected 5 clusters based on Elbow and Silhouette method.
3. Generated summary/descriptive statistics for each cluster.
4. Applied Logistic Regression, Lasso-based Regression, and kNN modeling for each cluster.
5. Used performance measures such as recall, precision, accuracy, and F-measure.

Data Gathering

Parameters	Description
Site	Location part is used in manufacturing
Supplier	Company the part is purchased from
Part	Unique Part Number
Cost	Cost of purchasing part
Reorder point (ROP)	Quantity at which inventory is re-ordered
Quantity Available	Current stock available
Days on Inventory (DOI)	Quantity available to support manufacturing for 2 days
Workweek (WW)	Calendar workweek (i.e. WW1 = first week of the year)
Category	Rating given to part based on purchasing history
Leadtime	Amount of time to get part from the supplier to the warehouse
Zero Bin (Predicted)	Variable created to identify whether a part has zero bin for that WW
Log	Inventory available in the previous week

Fig. 3 Analyzed Parameters

Results & Discussion

Fig. 4 Confusion Matrix

Fig. 5 Logistic Regression Confusion Matrix Cluster 0

Fig. 6 Logistic Regression Confusion Matrix Cluster 1

Fig. 7 Logistic Regression Confusion Matrix Cluster 2

Fig. 8 Logistic Regression Confusion Matrix Cluster 3

Fig. 9 Logistic Regression Confusion Matrix Cluster 4

Application Towards I.O.T/Smart Manufacturing

- This research was inspired by the lack of wholistic understanding amongst stakeholders of the issues that cause parts to go to zero-bin.

- By exercising the three paradigms of Industry 4.0: the smart product, the smart machine, and the augmented operator decision making can be made in real time to prevent critical manufacturing inventory outages.

Fig. 11 represents a high-level overview of the manufacturing process

- With data being collected at every step of the way, stakeholders will come together: inventory managers, operations, and suppliers to ultimately lead to optimized manufacturing throughput, and higher company profits.

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Acknowledgements

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- Special thanks to Intel's SPSC department manager Dr. Subramani Iyer, and my UTEP committee Dr. Megan Vaughan Kendall, Dr. Jose F Espiritu Nolasco for their guidance in the research process.

- A special recognition to my Python tutor William James McGinn.

Fig. 1 Spare Parts Supply Chain

Fig. 2 Zero Bin Problem

Fig. 3 Analyzed Parameters

Fig. 4 Confusion Matrix

Fig. 5 Logistic Regression Confusion Matrix Cluster 0

Fig. 6 Logistic Regression Confusion Matrix Cluster 1

Fig. 7 Logistic Regression Confusion Matrix Cluster 2

Fig. 8 Logistic Regression Confusion Matrix Cluster 3


Fig. 9 Logistic Regression Confusion Matrix Cluster 4

Fig. 10 Elbow Method

Fig. 11 Silhouette Method

Fig. 12 Clustering Results

TOOLS AND TECHNIQUES FOR EFFICIENT ENERGY USE IN VERTICAL FARMING



Tools and techniques for efficient energy use in vertical farming

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¹ Department of Industrial, Manufacturing & Systems Engineering (IMSE)
² Consortium of Hybrid Resilient Energy Systems (CHRES)
The University of Texas at El Paso

Research/Project Objective

Investigate how to monitor and analyze vertical farming data through applications, data analysis and software. Understanding the design of efficient and cost-effective vertical farming research of inputs and outputs, and optimization of farming through the use of technology.

Background

As the human population is overgrowing, the food demand worldwide has been increasing over the years. However, expensive agricultural tools, reduced availability of farming lands, uncertain farming output, and effects of climate change have adversely impacted food generation. Vertical farming comes as a solution that uses various techniques such as hydroponics, aeroponics, and aquaponics farms.

Research /Project Design

- Research vertical farming components
- Learning about energy sources
- Learning data analysis and different software applications
- Learning data science languages

Data Gathering/Analysis

Handling of data through Julia, Jupyter, Python, MATLAB and Simulink

Fig. 1 Data Handling

Results & Discussion

Vertical farming is an eco-friendly solution, capable to use wind and solar energy resources. . It is the best option for sustainability, alleviating poverty, environmental, geographical problems, and the future for wind and solar energy regarding the utilization of energy. Vertical farming reduces water usage, maintains less exposure to chemicals, optimizes space, uses data science, facilitates vertical farming systems and organizes data. Technology is key for healthy growth of plants in any environment.

Conclusions & Future Work

Vertical farming is a complex system that uses innovative technology and its research has been accomplished by tools & techniques. Future potential research include farming information control through complex coding languages, advance in the usage of renewable resources, adaptation in forms renewable energy (as microgrids in extreme environments and rural areas), and models development to evaluate various conditions.

Methods


- Facilitate the technical, logistics, analysis and management (GreenR, Autogrow, GP Solutions, LettUsGrow)
- Optimize vertical farming design and components through solar panels, generators and wind turbines (Homer Energy)
- Usage of tools to control lighting, CO2, nutrients, pH levels, air temperature, flood, fires, humidity, fans, water temperature, flow & levels (Greenery and CropBox)
- Calculating return of investment through farming investment calculator

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Acknowledgements

This research is supported by the Consortium of Hybrid Resilient Energy Systems (CHRES).



TMAC-PASO DEL NORTE

RESOURCES FOR LOCAL SMALL & MEDIUM MANUFACTURERS

TMAC Paso del Norte is a public-private partnership located at UTEP to serve a wide range of businesses including manufacturing, healthcare, and government. TMAC's mission is to increase the global competitiveness of the Texas economy by working to grow and sustain the extended manufacturing enterprise. TMAC works with companies to help them advance and make operations more agile by using Lean, Quality, Supply Chain, and Workforce Development practices. TMAC PdN provides lean and efficient customized solutions that deliver a competitive edge, identify growth opportunities, and foster regional economic development.

TMAC delivers hands-on business management, technology and operations solutions to a wide range of businesses, including manufacturing, distribution, logistics, construction, health care and government. We have a wide array of services that accelerate profitable growth by developing and improving products, processes and people. Focus areas include Strategic Management, Technology and Operations.

PUBLIC PRIVATE PARTNERSHIP

TMAC is an affiliate of the Manufacturing Extension Partnership (MEP) program of National Institute of Standards and Technology (NIST).

The National Institute of Standards and Technology's Hollings Manufacturing Extension Partnership (MEP) works with small and mid-sized U.S. manufacturers to help them create and retain jobs, increase profits, and save time and money. The nationwide network provides a variety of services, from innovation strategies to process improvements to green manufacturing. MEP also works with partners at the state and federal levels on programs that put manufacturers in position to develop new customers, expand into new markets and create new products.

MEP field staff has over 1,300 technical experts – located in all 50 states and Puerto Rico – serving as trusted business advisors, focused on solving manufacturers' challenges and identifying opportunities for growth. As a program of the U.S. Department of Commerce, MEP offers its clients a wealth of unique and effective resources centered on five critical areas: technology acceleration, supplier development, sustainability, workforce and continuous improvement.

TMAC offices are strategically located across Texas.



OUR APPROACH MAKES US DIFFERENT

Our TMAC advisors have several decades of combined industry experience. Their knowledge and expertise encompasses vast technical, innovative, operational and support areas within an organization. Because of TMAC's hands-on approach, our advisors understand the issues customers face on a daily basis.

TMAC doesn't leave a to-do list for you to navigate alone. We work with you to achieve dramatic results. Our objective is not to implement these methodologies to you or for you, but rather with you to develop your in-house expertise so that improvements are sustainable.

WORK SMART, GROW SMART

TMAC's mission is to increase the global competitiveness of the Texas economy by working to grow the extended manufacturing enterprise.

TMAC works with you to make your company more efficient, whether it is energy efficiency, quality issues, or supply chain, we will give you the customized solutions to have the competitive edge, discover financial opportunities and grow your business.

In today's super competitive environment, growing a business requires planning, efficient processes, customer focused innovation, new customers and markets and smart financial decisions. Whether you desire assistance in one area or a comprehensive approach, TMAC provides actionable steps to get you to the next level and beyond.

TMAC SOLUTIONS

- Executive Leadership
- Supply Chain & Logistics
- Product Development
- Operations
- Maintenance & Facilities
- HR
- Finance & Accounting
- Administration

THE **5** PILLARS OF TMAC

PROFIT
PRODUCT
PROCESSES
TECHNOLOGIES
PEOPLE

ECONOMIC IMPACT

MEP Center impacts are based on clients surveyed in FY2020

\$528.6 Million

Total Increased/Retained Sales

5,259

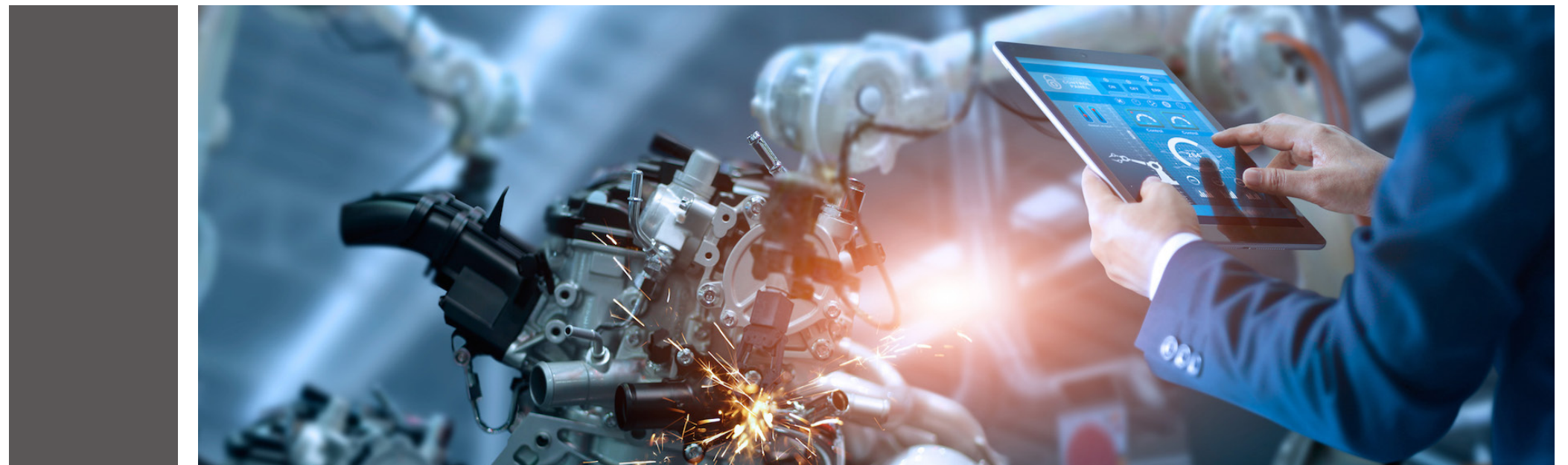
Total Increased/Retained Jobs

\$207.3 Million

New Client Investments

\$170.6 Million

Cost Savings

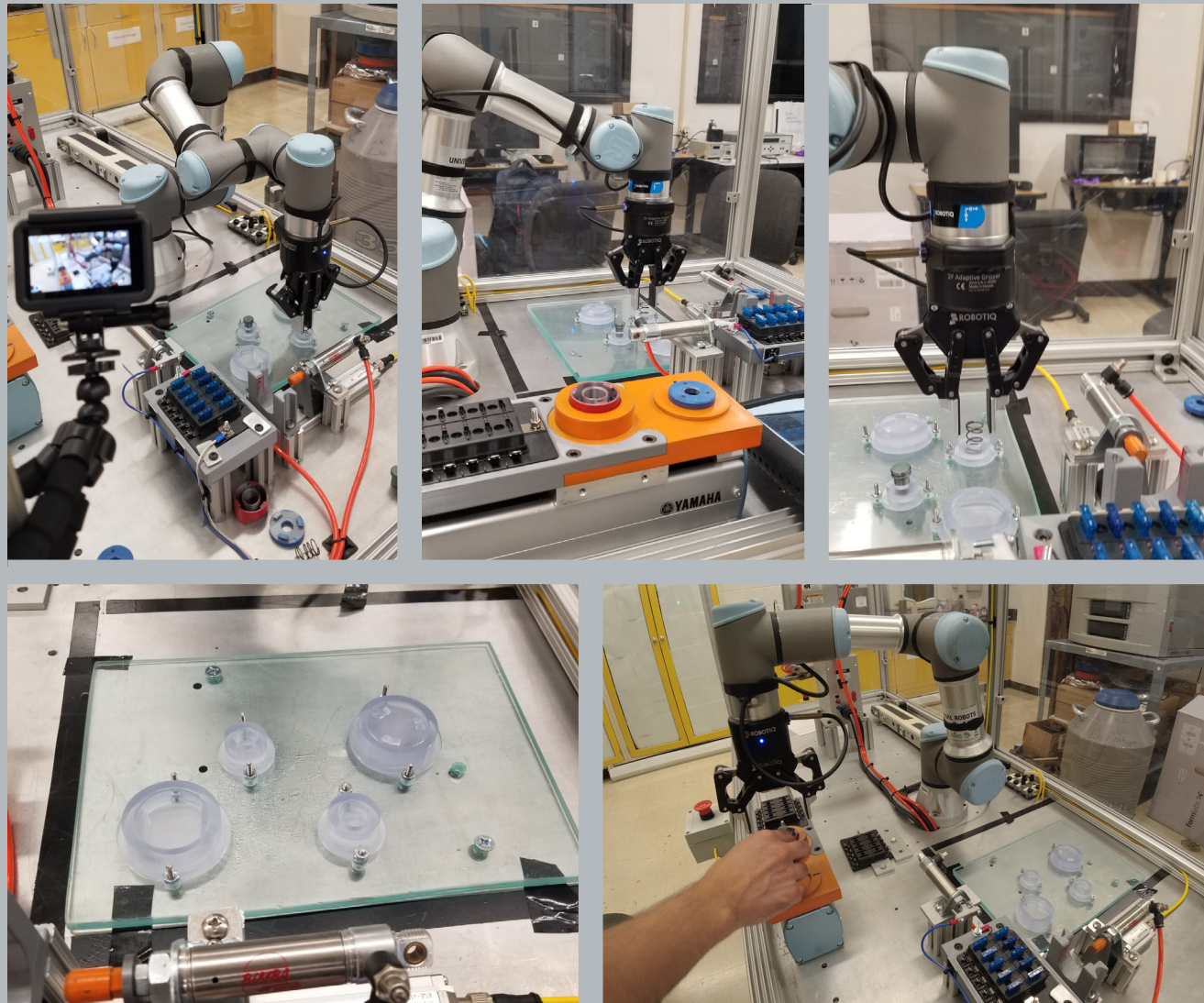


SMART MANUFACTURING LABS

INNOVATION LAB

The U.S. manufacturers face many challenges and one of the most impactful is the limited number of skilled workers to support machine automation and robotics in their factories. Hence, this Smart Manufacturing setup is intended to be used to teach the fundamental of industrial robots and automation.

The main objective is to teach a novice an introduction to Programmable Logic Controllers (PLCs), Human Machine Interfaces (HMIs), and collaborative robots programming. Simatic step 7 and Simatic WinCC are used to teach the fundamentals of ladders diagram and HMI programming, respectively. Moreover, the integration of different technologies is covered. For instance, students will learn Human Machine Interface development and integration with ladder diagrams. Lastly, students will be introduced to the industrial applications of collaborative robots and its programming.



DIGITIZATION OF MANUFACTURING SYSTEMS

Through this hands-on activity, students will learn the implementation of an IO Link platform to establish a remote connection into an advanced additive manufacturing system and extract thermal signatures that are an important component of the quality of the manufacturing process. The implementation will be done in an electron beam powder bed fusion (EB-PBF) manufacturing system that is employed in the fabrication of metal components at elevated temperatures.

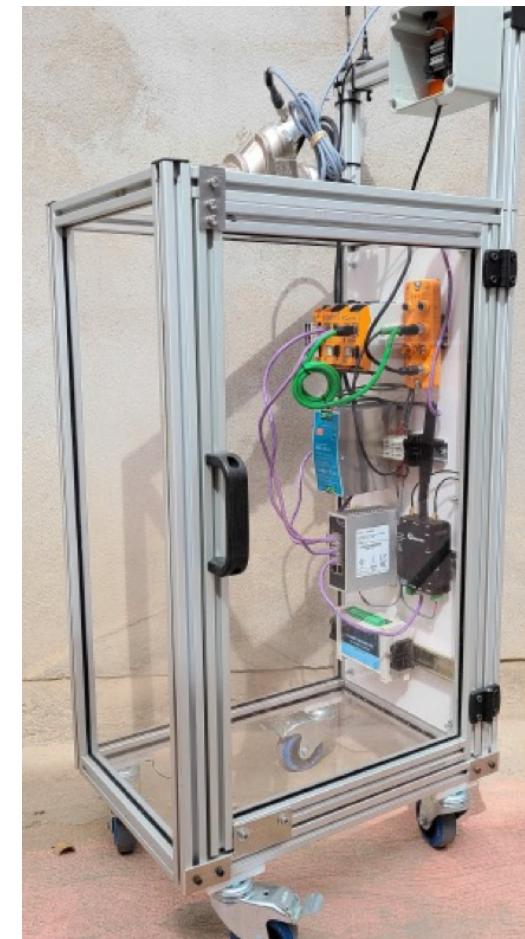
Thermal signatures will be monitored and transferred into a cloud server using the NODE RED visual environment from which students will subscribe, download data, and perform analysis to detect anomalies during the fabrication process. Students will also develop a mobile/email alert system that is triggered and informs on processing anomalies.

SOFTWARE USED

- NODE RED
- Node JS
- IO Link / MQTT data transfer protocols

TOOLS & SENSORS

- Industrial EB-PBF
- Raspberry PI*
- NI cDAQ temperature module
- Type K, thermocouples



SMART MANUFACTURING CERTIFICATE PROGRAM

With access to the fifth largest manufacturing hub in North America, creating a Smart Manufacturing (SM) curriculum to attract and grow an advanced manufacturing educated workforce, particularly in underserved small and medium manufacturers is critical. The Industrial Manufacturing and Systems Engineering department at The University of Texas at El Paso is creating a certificate and training program, specifically focused on skillsets and competencies needed for effective SM technology adoption and implementation. The proposed SM certificate will include five core courses, including two electives, covering key SM related topics with hands-on exercises in SM technologies and techniques.

The courses that will be part of the SM certificate program include:

1

INTRODUCTION TO SMART MANUFACTURING TECHNOLOGIES

This introductory course will provide an overview of the various aspects of smart manufacturing and will emphasize the use of several SM technologies for optimizing manufacturing operations. This course will teach the basics of each SM technology including design considerations, advantages, and limitations.

2

INDUSTRIAL DATA ANALYTICS AND MACHINE LEARNING FOR SMART MANUFACTURING

Data analytics is affecting productivity, innovation, and revenue by transforming data into insights for making better business decisions. This course will cover common data analytics techniques: (1) data analytics basics, (2) data preprocessing, (3) mining patterns, (4) classification, (5) cluster analysis, and (6) software data mining and analytics using Python.

3

AUGMENTED REALITY/VIRTUAL REALITY APPLICATIONS IN SM

This course module covers the field of Augmented Reality (AR) and Virtual Reality (VR). AR allows merging of real world with virtual objects superimposed to enable Marker-based tracking and Marker-less tracking. VR is a simulation generated with the help of interactive software and hardware, which utilizes the controller and the Head Mounted Device (HMD) to replicate real-world scenarios for workforce training and design verification purposes.

4

DATA VISUALIZATION FOR DECISION MAKING

This course provides an introduction as well as hands-on experience in data visualization for students to design and create meaningful displays of quantitative/qualitative data to facilitate managerial decision-making. The course will include (1) data visualization principles, (2) data communication and effective presentation, (3) data visualization software tools, and (4) industry projects to identify, understand, analyze, prepare, and present effective visualizations.

5

DIGITIZATION OF MANUFACTURING SYSTEMS

This course will provide students with knowledge of embedded sensors and their interfaces with advanced manufacturing processes. The course will instruct students into the extraction of data from the manufacturing systems as well as engage them into the use of techniques for data processing, interpretation, and visualization. Throughout the course, students will interact with manufacturing equipment and employ data analysis techniques.

The newly acquired SMI lab and Additive Manufacturing systems within the W. M. Keck Center for 3D Innovation will be retrofitted with SM related technologies and APIs for facilitating SM research and development.



ALPHA PI MU

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To provide networking opportunities, technical resources, personal development experiences and recognition to enhance the skills and effectiveness of the industrial and systems engineering students.

