Strategy for Resilient Manufacturing Ecosystems Through Artificial Intelligence Workshop 2

Roundtable 3 'AI for Industry-Wide Data Sharing'

Dave Vasko
Director, Advanced Technology, Rockwell Automation

Roundtable Session
July 7, 2021
11:00 am – 3:00 pm ET

Salman Avestimehr
Professor & Director, USC-Amazon Center on Trusted AI, University of Southern California

Symposium Leads

James St. Pierre
NIST

Jim Davis
UCLA

Said Jahanmir
NIST

Don Ufford
NIST

AI for Industry-Wide Data Sharing
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Jenny Du, Professor, Electrical and Computer Engineering, Mississippi State University
Henry Kautz, Division Director, CISE/IIS, National Science Foundation
Chris Krampitz, Senior Director of Technology Strategy, MxD
Soundar Kumara, Allen, E, & M., Pearce Professor of IME, Penn State University, University Park
KC Morris, Group Leader, Information Modeling and Testing, NIST
Michelle Pastel, Senior Manager, Manufacturing 4.0, Corning
Sudarsan Rachuri, Technology Manager, Advanced Manufacturing Office, DOE
Maja Vukovic, IBM Fellow AI Research, IBM
Wei Wang, Professor and Director, Scalable Analytics Institute (ScAi), UCLA
Dave Dorheim, Head Workshop Writer
Yoh Kawano, Spatial Data Scientist/Research Consultant/Lecturer, Office of Advanced Research Computing, UCLA

Agenda

Timeline (EST)	Presenter and Topic	Duration
11:00AM – 11:10AM	**Symposium Co-Chair (James St. Pierre)**: Introductions and how the overall Workshop is coming together, statement of objectives and how the roundtable will work	10 mins
11:10AM – 11:30AM	**Roundtable Co-Chairs (Dave Vasko & Salman Avestimehr)** : Discussion framework and questions	20 mins
11:30AM – 1:30PM	**Roundtable Participants (All)**: Address questions	120 mins
1:30PM – 1:40PM	**Break**	10 mins
1:40PM – 2:00PM	**Roundtable Participants (All)**: Summarize findings and preparation for report out discussion (bullet points prepared by Organizing Committee member)	20 mins
2:00PM – 2:55PM	**Roundtable Co-Chairs (Dave Vasko & Salman Avestimehr)** : Report out and open discussion with roundtable and general participants: 1. Roundtable co-chairs report out 2. Q&A facilitated by roundtable co-chairs (bullet points prepared by Organizing Committee member)	55 mins
2:55PM – 3:00PM	**Symposium Co-Chair (James St. Pierre)**: Closing remarks	5 min

U.S. Advanced Manufacturing Competitiveness

CONVERGING DRIVERS

Global Leadership: Making the right products the right way, the first time, at the right time and place

Operations: Precision, productivity, performance, safety, products-as-a-service, manufacturing-as-a-service

Digitalization: Digital transformation and resurgence of AI

Sustained Pandemic Impacts: Supply chain resilience

Environment: Consumption, waste sustainability, climate change, carbon intensity

Security: National security, dependence, cybersecurity

ADVANCED MANUFACTURING COMPETITIVENESS

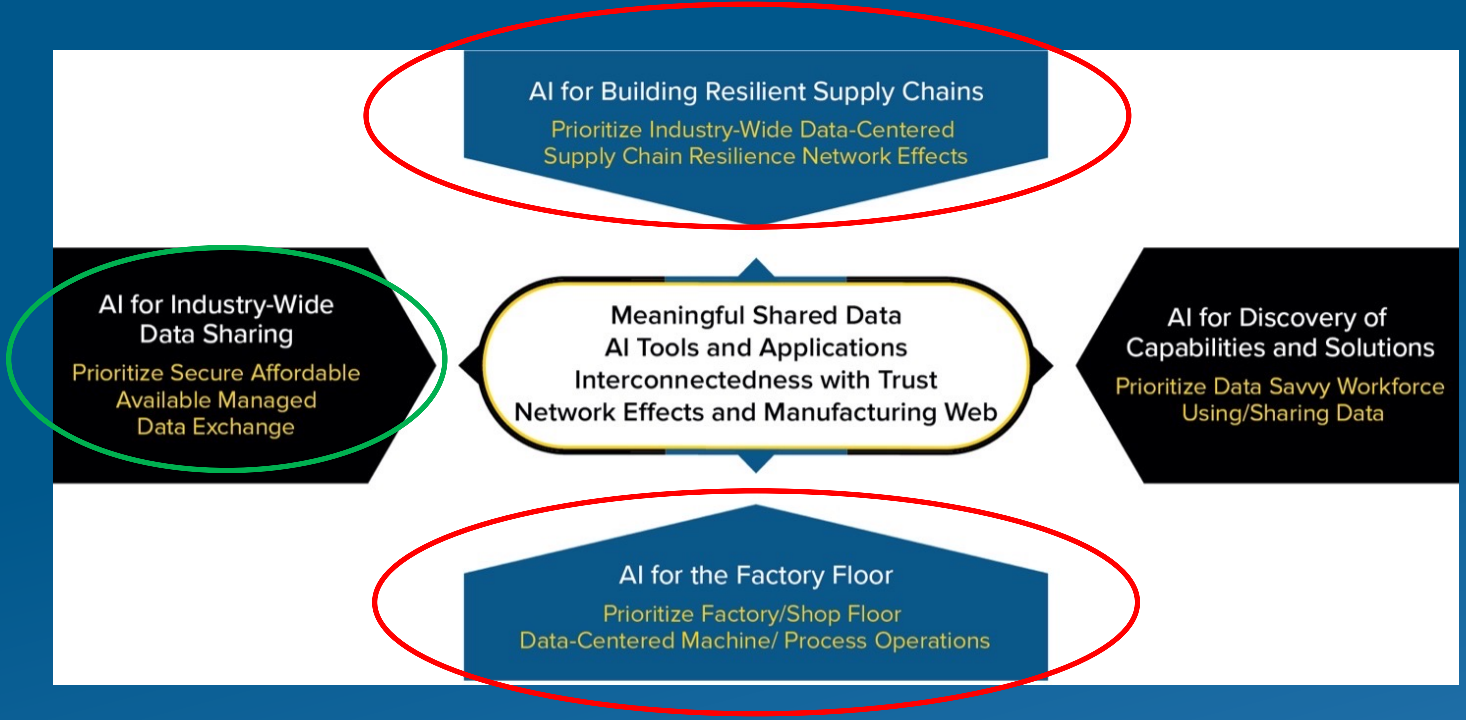
Manufacturing ecosystem resilience

Global competitiveness and economic market share

Reduced energy and material consumption; environmental sustainability

National cyber and data security and opportunity

Implementation Framework



Working Definitions

Artificial Intelligence (AI) in manufacturing refers to software systems that can recognize, simulate, predict, and optimize situations, operating conditions, and material properties for human and machine action.

Machine Learning (generally seen as a subset of AI) refers to algorithms that use prior data to accurately identify current state and predict future state, with the goal of improving productivity, precision, and performance.

Networking creates digital connections among devices, machines, equipment, databases, computer programs, and users, to provide the ***connectedness*** needed to exchange information, make decisions, and take actions.

Predictive Modeling is the use of data, AI, machine learning, simulation, and digital twins to assess, predict, and anticipate process, product, and operational behaviors for control, design, optimization, health, and failure prevention and mitigation.

Network Effects produce increased benefits for network users as the number of connected user nodes increases by expanding the availability of information and knowledge accessible to all.

A Resilient Supply Chain recovers quickly from an unexpected event*

*100-day-supply-chain-review-report.pdf (whitehouse.gov)

RT1 'AI for the Factory Floor'
June 15, 2021

Ram Sriram
Chief, Software & Systems Division
NIST

Jorge Arinez
Group Manager
GM, Research & Development

Jan de Nijs, LM Fellow for Enterprise Digital Production, Lockheed Martin
Vinod Kumar, Chief Engineer, Manufacturing, GE Aviation
Laine Mears, SmartState Professor of Automotive Manufacturing, Clemson University
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Alexandra "Alex" Cintrón, Raytheon Space & Airborne Systems Factory Automation Manager
Ani Parthasarathy, Principal, kearney.com
Dave Rapaport, Head of Research and Collaboration Management, Siemens
Juan Aparicio, VP of Product, READY Robotics
Soundar Kumara, Professor, Industrial Engineering, Penn State University

RT1 Draft Findings

When differentiating “AI for the Factory Floor” applications in terms of hard dollar vs. soft dollar economic benefits, quality assurance remained a top priority. Quality assurance is also comprehensive with end-to-end supply chain dependency. Predictive maintenance and other cost reductions opportunities and supporting remote work were discussed as priority opportunities.

The successful AI Factory Floor project starts with a well-defined problem statement. A well-formed problem statement is an essential success factor and is essential to communicating and substantively planning value proposition and strategy together. Categorizing opportunities by problem statement is as important as categorizing them by application area.

All aspects of data need to be managed and shared (multiple forms) to build the tools and algorithms for successful AI adoption. Data must be trusted, relevant, protected, and accessible. This requires a data exchange marketplace using a supply/demand model with appropriate incentives for data providers.

Academic institutions have significant untapped capability in AI adoption. This includes capability to educate and train workforce broadly from floor operators, to engineers, to data and knowledge workers, to legal professionals and new ways to transfer learning. This includes capability to develop and benchmark scaled tools, methods and algorithms: automate contextualize data formulation, build secure models, demonstrate standards, build algorithms for common applications.

RT2 'AI for Building Resilient Supply Chains'
June 29, 2021

John Dyck
CEO
CESMII

Jayant Kalagnanam
Director, AI Applications
IBM Research

Jim Wetzel, Co-Founder, NxGen Group
Ganesh Bora, National Program Leader, National Institute of Food and Agriculture, U.S. Department of Agriculture
Brad Nicholas, Director, Digital Platforms, IT Emerging Technology, Corning
Larry Megan, Vice President, Advanced Manufacturing International (formerly Praxair)
Lance Fountaine, Global Operations Automation, Digitalization, and Analytics Leader, Cargill
Heather Siflinger, Data Scientist, Boeing
David Womble, Program Director, AI Initiative, Oak Ridge National Laboratory
Steve Chien, JPL Fellow, Senior Research Scientist, AI, Autonomous Systems, NASA JPL
Jim Watson, President and CEO, California Manufacturing Technology Consulting (CMTC)
David Gonsalvez, CEO and Rector, Malaysia Institute for Supply Chain Innovation
Brian Tomlin, Senior Associate Dean, Faculty and Research, Tuck School of Business, Dartmouth
Jack Prior, Head, Industrial Affairs Specialty Care MSAT Digital, Sanofi
Andrew Browning, Technical Writer, Office of Advanced Research Computing, UCLA
Dave Dorheim, Head Workshop Writer

RT2 Questions

What about resilient supply chains should we develop, measure, and make transparent to motivate both innovation (new supplier, product, capability opportunity) and resilience and how do we do it?

1) ***The highest value propositions for AI in the resilient supply chain are generally characterized as multi-supply chain, inter-manufacturer visibility and cross supply chain monitoring and analytics. What do we mean by these and why would the industry want to change)?***
2) ***We agree that "AI" can facilitate the supply chain value propositions above (operational optimization, market identification opportunity, business agility). How do business models, value propositions, and industry capabilities align to motivate manufacturers to <u>want</u> to interact)?***
3) ***What are the business models for scaled AI implementation for SMM engagement in the resilient supply chain so all manufacturers can participate in the ecosystem data and models***?

RT3 Starting Premises from Workshop 1

We agree that industry-wide data sharing for AI data and modeled system solutions are needed. What do we mean by this in terms of what solutions are needed and what problems will be solved?

We agree that managing and having ways to exchange and combine curated data is key. What data need to be shared and what methods, tools, standards, and research are needed for security, protection, and trust?

The following manufacturing areas for AI and industry-wide data exchange have been articulated:

a) Data exchange for interoperability among manufacturers for peer-to-peer product and productivity across a supply chain
b) Data exchange for supply chain visibility and cross-industry analytics
c) Open data sharing – sharing and combining data and/or models for benchmarking, training and testing, algorithms, methods and tools, i.e. images for testing feature extraction approaches
d) Combining on and scaling data and modeled systems for providers of common machines and operations used on the factory floor
e) Improving quality assurance of product and materials while they are being made

We agree there needs to be business models, agreements, and organization and workforce changes for manufacturers to participate in an adoption cycle that leads to the generation and sharing of data that are necessary to develop AI models for scaled use.

RT3 Questions

1. ***Why do we want to share data as an industry (e.g. weather data, cancer data, financial data)?***
   How do you categorize the specific types of manufacturing challenges or opportunities with respect to greatest benefit and readiness or ability to share and combine data for AI applications; what curated/contextualized data are of greatest value and how do we position for scaled availability and use of curated data?

2. ***How do we share data?***
   With respect to the current options, how do they align with scaled use of shared data and AI models in a secure and privacy-preserved manner while providing assurances of intellectual property protection to cultivate trust across the industry?

3. ***What drives/motivates the sharing of data?***
   What are the business models for data sharing adoption to start and accelerate scaled AI implementation in the SMM supply chain so all manufacturers can participate in the ecosystem of data and models?

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1. ***Why do we want to share data as an industry (e.g. weather data, cancer data, financial data)?***

   How do you categorize types of manufacturing challenges or opportunities with readiness or ability to share and combine data for AI applications; what curated/contextualized data are of greatest value and more readily shared; how do we position for scaled availability and use of curated data?

   a) What are the value propositions and how are they best explained/approached with small, medium, and large manufacturers to compel investment in an adoption journey?
   b) What do we mean by contextualized data? How do we address value proposition in terms of contextualized data (i.e. not just assume the right data are available)?
   c) We agree on the AI opportunities – (1) quality assurance and asset management on the factory floor, (2) visibility and analysis of the supply chain, and (3) industry-wide strategies for building models and tools for the most discussed – can we characterize what are the problem statements, what kinds of modeling are to be used, what data are to be shared, what are the sources of data, and how would the data need to be curated.

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RT3 Questions

2. ***How do we share data?***
   With respect to the current options, how do they align with scaled use of shared data and AI models in a secure, ethical, and privacy-preserved manner while providing assurances of intellectual property protection to cultivate trust across the industry?
   a) What are the options for facilitating global data exchange when considering the priority areas in the premise section?
   b) With respect to specific techniques, how do you consider data-oriented techniques, i.e. synthetic data (e.g. GAN), encryption, federated learning, etc. vs. sharing models and model building.
   c) How do you consider federated vs. pooled data sharing approaches for building the needed level of trust? Or is it context dependant?
   d) Are current security and privacy-preserving techniques effective (e.g., differential privacy) and sufficient?
   e) What lessons can be learned/applied from other industries' approaches to secure and privacy-preserved data sharing?
   f) How are the trust and security propositions best explained/approached with small, medium, and large companies to compel investment in adoption journey?

RT3 Questions

What drives/motivates the sharing of data?

What are the business models for data sharing adoption to start and accelerate scaled AI implementation in the SMM supply chain so all manufacturers can participate in the ecosystem of data and models?

RTT3 Questions

3. ***What drives/motivates the sharing of data?***
   What are the business models for data sharing adoption to start and accelerate scaled AI implementation in the SMM supply chain so all manufacturers can participate in the ecosystem of data and models?
   a) We agree that supply chain and factory floor AI application opportunities heavily depend on SMMs so what is needed to involve and scale SMM engagement with contextualized data.
      I. What are the roles for
         - Large OEMs?
         - SMMs?
         - Providers
         - Public-private partnerships
         - Government
      II. What research, technology, or tools are needed to better enable AI and data for SMMs?
   b) We agree on contextualized data sharing for industry-wide purposes, i.e. an ecosystem of scaled curated data
      I. Who needs to do what for this to happen?
      II. If data privacy, integrity, and security are addressed, are we talking about provider-based AI and data services and an industry data supply chain and exchange?
   c) Are there governance models that would help accelerate manufacturing adoption of AI and sharing of data and models?
      I. What is the role of public-private partnerships?
      II. What is the role of government?

Break

1:30 PM – 1:40 PM

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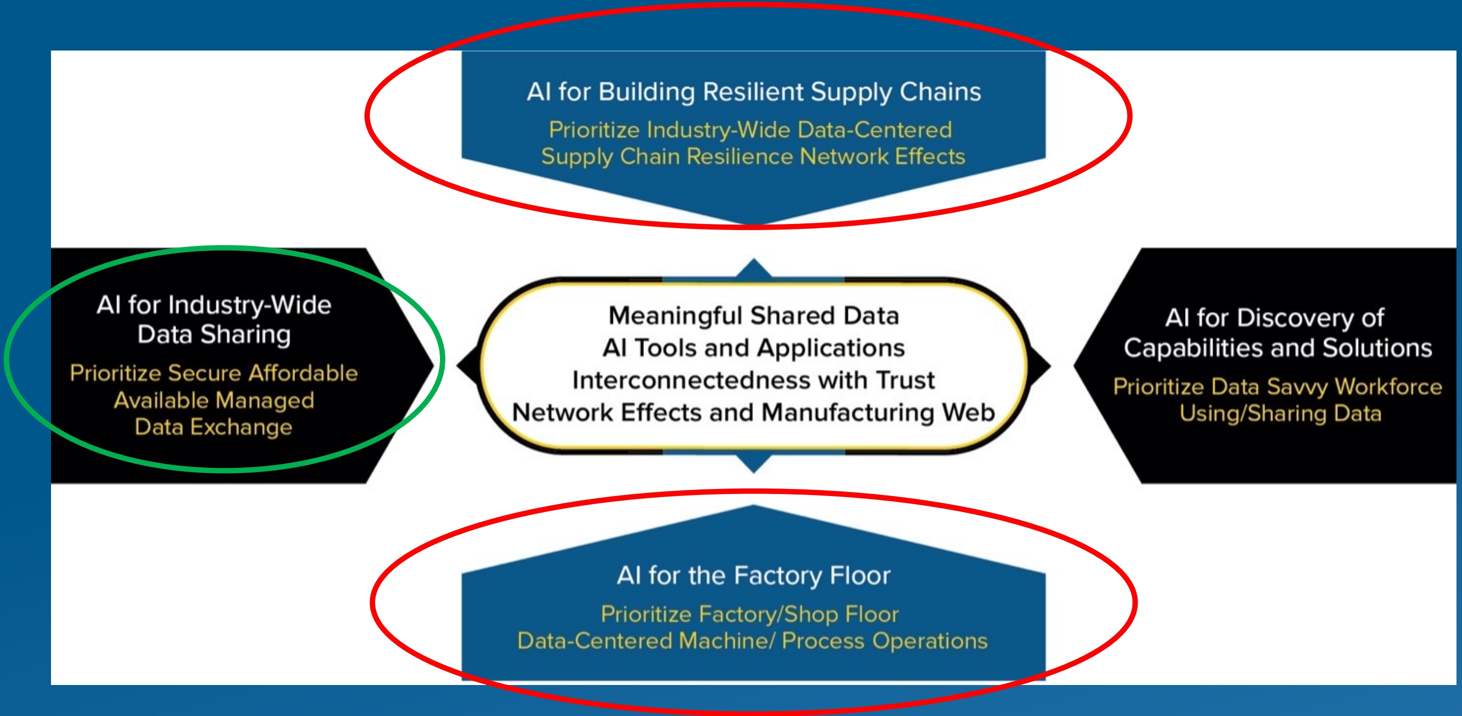

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- Within industry we can learn about user interface issues, user experience and opportunities for improvement.
- Industry may want to share data but is concerned about the unintended consequences (e.g. data set can be used to reverse engineer the part). What research can be done to help mitigate?
- Network building block relationships and interconnections can be important to build motifs for forming a decision.
- Manufacturers need guidance to start their AI journey and what data to collect, how it can be analyzed and then utilized.
- If the machine manufacturer can share data with the end-user and vice versa, AI models may be trained faster and predict maintenance and quality issues with more precision.
- Manufacturing maintenance logs in natural language have been examined by NIST and offer an AI opportunity that may be less likely to experience reverse engineering.
- How can AI help guide knowledge extraction from subject matter experts. Can it be generalized or is the issue machine specific? Can an AI assistant help interview people.
- Gamification of data collection and supplied information usage incentivization for the worker to support AI?
- User friendly ontologies could be used as a mapping tool.
- Quality assurance in additive manufacturing could deliver value using AI to optimize the machine material interaction for each layer.
- Data can facilitate research

RT3 Questions

2) How do we share data?

With respect to the current options, how do they align with scaled use of shared data and AI models in a secure and privacy-preserved manner while providing assurances of intellectual property protection to cultivate trust across the industry?

- Why is there a disparity in the extent of data sharing across sectors and what can we do to enable manufacturing data sharing to a larger extent?
- Use cases where manufacturers benefited from other manufacturers could help others understand the benefits and value of data sharing.
- If the use case or demo is difficult to scale/generalize, its impact will be limited both internal and external to the manufacturer.
- Protecting data security vs. privacy may require different levels of protection.
- Common data standards, ontologies are needed for meta data structures to be effectively shared.
- Legal liability issues need to be understood and/or mechanisms like “Data Trusts” could be used.
- How do we leverage small size data that may be complex with large data with high signal to noise ratio and low dimensionality?
- Data generation needs to consider the complexity of the source and not lose the richness.
- Would federated learning help alleviate intellectual property issues? Should data from USG grants be broadly available?
- Receiver of data needs to be able to trust the data (source, maintenance and communication). Standards and methods to maintain trust in the data chain need to be developed.
- Smaller, focused data cooperatives may be a good way for SMMs to store and share data.
- Data curation is required.

RT3 Questions

3) What drives/motivates the sharing of data?

What are the business models for data sharing adoption to start and accelerate scaled AI implementation in the SMM supply chain so all manufacturers can participate in the ecosystem of data and models?

- If the use case is understood and valued, there is much more interest in supporting with data.
- SMM adoption is often driven by the large OEMs who have developed successful use cases and cascaded the requirements.
- SMMs are concerned that they will not have enough resources to support multiple unique OEM processes.
- Certification and validation company relationships may offer a view of how to handle proprietary data.
- SMMs will be motivated by a return on investment and the ability to connect with their supply-chain.
- Non-certified/regulated industries/processes may offer a white-space for data sharing.
- Digital twin of a manufacturing process could be a strong motivator for the sharing of data.
- Clearly restricting or limiting the use of the data is a must.
- Requiring government funded research to provided curated data could provide a foundational trusted data set.
- SMMs are concerned they will be priced out of the market as AI applications become more prevalent.
- Bottom-up: recognize SMM needs, develop the right incentives, build track-record of success.
- Sustainability requirements may require more data sharing.

Upcoming Roundtable Sessions

Date	*Roundtable*
June 15th	AI for the Factory Floor
June 29th	AI for Building Resilient Supply Chains
July 7th	***AI for Industry-Wide Data Sharing***
July 19th	AI for Discovery of Capabilities and Solutions

Thank You

Please send comments to: AIengineeringworkshop@oarc.ucla.edu

Visit our website:

https://oarc.ucla.edu/nsf-nist-symposium

Co-Chairs:
Jim Davis, UCLA
Stephan Biller, AMI
James St. Pierre, NIST