From Data to Insight: Big Data and Analytics for Smart Manufacturing Systems

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Outline

• Smart Manufacturing System Design and Analysis
  – Program objective and focus
  – Program Thrusts and Projects

• Projects
  – Reference Architecture
  – Modeling Methodology
  – Predictive Analytics - Big data analytics for manufacturing
  – System Performance Assurance
Smart Manufacturing Systems Design and Analysis

Models and standards for Smart Manufacturing Systems Design and Analysis

- SysML, BPMN, Modelica
- Standards and Measurement Science
- Reference Architecture
- OAGi standards
- ISA 95

Performance Assurance for Smart Manufacturing Systems

- Performance metrics and Standards
- ASTM E60.13
- Real-Time Data Analytics
- Performance of SMS

- Energy
- Material
- Product
- Waste
Projects – Short description

• Reference Architecture
  – Provides a common vocabulary and taxonomy, a common (architectural) vision, and modularization and the complementary context. - Composability

• Modeling Methodology
  – The new technical idea is to bring together the conceptual modeling, information modeling, and behavior modeling paradigms - Compositionality

• Predictive Analytics
  – Big data analytics for manufacturing

• System Performance Assurance
  – Extending quality assurance to performance metrics, including tools for verification and validation.

An architecture is said to be composable with respect to a specified property if the system integration will not invalidate this property, once the property has been established at the subsystem level. A highly composable system provides recombinant components that can be selected and assembled in various combinations to satisfy specific user requirements.

Compositionality - The property of the system that the whole can be understood by understanding the parts and how they are combined.
Reference Architecture – ISA 95

- Business & User Goals
- Modeling & Optimization
- Data Analytics
- Control System(s)
- Sensors
- Physical System

Physical Environment

ISA-95, Image courtesy: Automation world
Model of Manufacturing System

Physical Artifacts
- Raw materials
- Components
- Auxiliary materials

Information Artifacts

Resources
- Energy
- Water

Emissions

Control

Predict

Physical Products
- Co-products
- By-products
- Waste

Information Artifacts

Resources

M1 – Machine 1

Mi – Machine i

Σ Pi – Process i
Performance Assurance for Smart Manufacturing Systems (PASMS)

- 5% decrease in batch cycle time
- 10% improvement in machine reliability
- 10% reduction in water consumption
- 5% reduction in energy costs

Source: www.ge-ip.com
A lot of Media and Business coverage of Big Data Analytics

Those that adopted “data-driven decision making” achieved productivity that was 5 to 6 percent higher than could be explained by other factors, including how much the companies invested in technology – Brynjolfsson, Erik, Lorin Hitt, and Heekyung Kim, Strength in Numbers: How Does Data-Driven Decision Making Affect Firm Performance? (April 2011)

‘The high-performing organization of the future will be one that places great value on data and analytical exploration’ (The Economist Intelligence Unit, ‘In Search of Insight and Foresight: Getting more out of big data’ 2013, p.15).

Data is a core asset
Companies that gain a competitive edge with analytics can be found at all levels of technological sophistication

“The evidence is clear, Data Driven Decisions tend to be better decisions. In Sector after Sector, companies that embrace this fact will pull away from rivals” – Big Data Management Revolution, Harvard Business Review

• Data Representation
• Computational Complexity
• Statistical and machine learning techniques
• Data sampling, cleaning
• Human in the loop

• Up to 50% reduction in product development and assembly cost
• Up to 7% reduction in working capital

Unleashing the Power of Big Data: Why We Need All Hands on Deck

Thomas Kalil
Deputy Director for Technology and Innovation
White House Office of Science and Technology Policy & National Economic Council
ntalPolicy.stp.gov
May 3, 2013
Manufacturing Big Data Analytics

- ROI of Big Data Analytics in Manufacturing Lifecycle
- Data availability and quality
- Distributed Computing Infrastructure
- Bring Manufacturing Science and Data Science closer
Exhibit 2

Some sectors are positioned for greater gains from the use of big data

Historical productivity growth in the United States, 2000–08

\[
\text{Big data value potential index}^1
\]

1 See appendix for detailed definitions and metrics used for value potential index.

Data Analytics Across Manufacturing Life Cycle

- DESIGN
- MANUFACTURING
- Supply Chain
- Supply Chain
- Post Use
- Use
We have identified the following big data levers across the manufacturing value chain:

<table>
<thead>
<tr>
<th></th>
<th>R&amp;D and design</th>
<th>Supply-chain mgmt</th>
<th>Production</th>
<th>Marketing and sales</th>
<th>After-sales service</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Build consistent interoperable, cross-functional R&amp;D and product design databases along supply chain to enable concurrent engineering, rapid experimentation and simulation, and co-creation</td>
<td>✔</td>
<td></td>
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<tr>
<td>2</td>
<td>Aggregate customer data and make them widely available to improve service level, capture cross- and up-selling opportunities, and enable design-to-value</td>
<td></td>
<td>✔ ✔ ✔</td>
<td></td>
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<tr>
<td>3</td>
<td>Source and share data through virtual collaboration sites (idea marketplaces to enable crowd sourcing)</td>
<td>✔</td>
<td></td>
<td></td>
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<tr>
<td>4</td>
<td>Implement advanced demand forecasting and supply planning across suppliers and using external variables</td>
<td></td>
<td>✔ ✔ ✔</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Implement lean manufacturing and model production virtually (digital factory) to create process transparency, develop dashboards, and visualize bottlenecks</td>
<td></td>
<td>✔ ✔ ✔</td>
<td></td>
<td></td>
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<tr>
<td>6</td>
<td>Implement sensor data-driven operations analytics to improve throughput and enable mass customization</td>
<td>✔</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Collect after-sales data from sensors and feed back in real time to trigger after-sales services and detect manufacturing or design flaws</td>
<td>✔ ✔ ✔</td>
<td></td>
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</tbody>
</table>

SOURCE: McKinsey Global Institute analysis
Huge Amount of Stored Data in Manufacturing: But converting Data to information assets is a challenge

Companies in all sectors have at least 100 terabytes of stored data in the United States; many have more than 1 petabyte

<table>
<thead>
<tr>
<th>Stored data in the United States, 2009</th>
<th>Number of firms with &gt;1,000 employees</th>
<th>Stored data per firm (&gt;1,000 employees), 2009</th>
</tr>
</thead>
<tbody>
<tr>
<td>Petabytes</td>
<td>Terabytes</td>
<td>Terabytes</td>
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<td>Discrete manufacturing</td>
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<td>967²</td>
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<td>Government</td>
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<td>Communications and media</td>
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<td>Process manufacturing</td>
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<td>Securities and investment services</td>
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<td>3,866</td>
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<td>Retail</td>
<td>364</td>
<td>697</td>
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<tr>
<td>Education</td>
<td>269</td>
<td>319</td>
</tr>
</tbody>
</table>

May 2011 | by James Manyika, Michael Chui, Brad Brown, Jacques Bughin, Richard Dobbs, Charles Roxburgh, Angela Hung Byers
We need to achieve data compression and timeliness across Layers

Data Compression

Kilobytes/second

Processing

Petabytes → Exabytes

Gigabytes → Terabytes

Intelligent data reduction

Filters

Gigabytes → Terabytes

Intelligent data reduction

Filters

Petabytes → Exabytes

Decision

Business and User Goals
Manufacturing Business Intelligence (web, desktop, mobile apps),
Dynamic production system, Operations

Integration

Rules Engine, Distributed and real-time computing, Apps, APIs, Web Services

Analytics

Predictive Models, Algorithms, Analytics engine, Model composition,
Uncertainty quantification

Data
Structured, multi-structured, Streaming, DAQ, Data pre-processing,
Descriptive analytics

Manufacturing Execution System, Manufacturing Operations Management
SCADA, PLC, HMI, DCS

*— Extraction, cleaning, annotation

Real time/On time

Years → Months → Weeks → Days

Hours → Minutes

Seconds or less

Manufacturing Business Intelligence (web, desktop, mobile apps),
Dynamic production system, Operations

Protocols/standards

Protocols/standards

Protocols/standards

Years → Months → Weeks → Days

Hours → Minutes

Seconds or less

SCADA Supervisory Control and Data Acquisition

PLC Programmable Logic Controller

HMI Human Machine Interface
We need standards and protocols

Required Standards and Technology

- Model Classification
- Model Tuning and validation
- Problem Classification
- Problem Commonalities
- Machine Learning/Training
- Data Classification
- Data of Data (meta-data)

Description

- Post Processing
  - Opt. (Time)
  - Opt. (Cost)
  - Simulation

- Data Analytics (Data Mining)
  - Asset Management
    - Problem a
  - Agility
    - Problem b
  - Sustainability
    - Problem c

- Data Preprocessing
  - Meta-Data
    - Data 1
  - Meta-Data
    - Data 2
  - Meta-Data
    - Data 3

Real Shop

Connected

Model (Output Layer)

Problem (Analytics Layer)

Data (Input Layer)
Reduce the information overload
Can we get the same level of insights with less data?

Data Volume

Past

Present

Future

Current DA

Big Data

Relevant and Useful Data
Acknowledgements

• Members of SMSDA Program