Smart Manufacturing Systems Design and Analysis

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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
  – System Performance Assurance

• Standards for SMSDA

• Collaboration Opportunities
Standards and Measurement Science for Smart Manufacturing Systems Design and Analysis

Models and standards
SysML, BPMN, Modelica

Performance metrics and Standards
ASTM E60.13

Performance Assurance for Smart Manufacturing Systems

Reference Architecture for Smart Manufacturing Systems

Standards Reference Architecture
OAGi standards
ISA 95

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

Real-Time Data Analytics for Smart Manufacturing Systems
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

Notional CPS Reference Architecture

- Functional, multi-stack architecture
- All layers should be co-designed in the context of the Physical Environment
- Management function, not depicted, provides oversight and ensures coordination and composability
Project: Modeling methodology for Smart Manufacturing Systems (MMSMS)

OBJECTIVE

• Develop modeling methodology and tools to predict, assess, optimize, and control the performance of smart manufacturing systems to result in a significant increase in process efficiency by FY 2018.

The new technical idea is to bring together the conceptual modeling, information modeling, and behavior modeling paradigms.
Project Three: Performance Assurance for Smart Manufacturing Systems (PASMS)

- **OBJECTIVE**
- To develop metrics and assessment methods that will assure the performance of dynamic production systems with a predictable degree of reliability by 2018.

Extending quality assurance to performance metrics, including tools for verification and validation.
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
Project Four: Real-Time Data Analytics for Smart Manufacturing Systems (DASMS)

OBJECTIVE

• Develop standards, methods, and protocols for data analytics to enable real-time diagnostics and prognostics that will significantly increase the efficiency of dynamic production systems by FY18.

Big data analytics for manufacturing
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)

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

‘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 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 Kall
Deputy Director for Technology and Innovation
White House Office of Science and Technology Policy & National Economic Council
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May 3, 2013
What is Big Data?

- **Volume**: Large quantity of data which may be enterprise-specific or general and public or private.
- **Variety**: Diverse set of data being created, such as social networking feeds, video and audio files, email, sensor data and other raw data.
- **Velocity**: Speed of data inflow as well as rate at which this fast-moving data needs to be stored.

Source: CRISIL GR&A analysis
Evolution of Analytics
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

Big data value potential index

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

Data Analytics Across Manufacturing Life Cycle
We have identified the following big data levers across the manufacturing value chain

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</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>
<td></td>
<td></td>
<td></td>
</tr>
<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>
<td>✔</td>
<td></td>
</tr>
<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>
<td>✔</td>
<td>✔</td>
</tr>
<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>
<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>
<td></td>
</tr>
<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>
<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>
<td></td>
<td></td>
<td>✔</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Sectors</th>
<th>Stored data in the United States, 2009 (Petabytes)</th>
<th>Number of firms with &gt;1,000 employees</th>
<th>Stored data per firm (&gt;1,000 employees), 2009 (Terabytes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discrete manufacturing</td>
<td>966</td>
<td>1,000</td>
<td>967</td>
</tr>
<tr>
<td>Government</td>
<td>848</td>
<td>647</td>
<td>1,312</td>
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<tr>
<td>Communications and media</td>
<td>715</td>
<td>399</td>
<td>1,792</td>
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<tr>
<td>Process manufacturing</td>
<td>694</td>
<td>835</td>
<td>831</td>
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<tr>
<td>Banking</td>
<td>619</td>
<td>321</td>
<td>1,931</td>
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<tr>
<td>Health care providers</td>
<td>434</td>
<td>1,172</td>
<td>370</td>
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<td>Securities and investment services</td>
<td>429</td>
<td>111</td>
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<tr>
<td>Professional services</td>
<td>411</td>
<td>1,478</td>
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<tr>
<td>Retail</td>
<td>364</td>
<td>522</td>
<td>697</td>
</tr>
<tr>
<td>Education</td>
<td>269</td>
<td>843</td>
<td>319</td>
</tr>
</tbody>
</table>

We need to achieve data compression and timeliness across Layers

Data Compression

Kilobytes/second

Processing

Petabytes → Exabytes

Gigabytes → Terabytes

Intelligent data reduction

Filters

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

Protocols/standards

Data

Megabytes

Intelligent data reduction

Filters

Years -> Months

-> Weeks

Days

Hours → Minutes

Seconds or less

Real time/On time
We need standards and protocols

**Description**

**Model (Output Layer)**

- Asset Management
- Agility
- Sustainability

**Problem (Analytics Layer)**

- Problem a
- Problem b
- Problem c

**Data (Input Layer)**

- Data 1
- Data 2
- Data 3

**Real Shop**

- Machine A
- Robot A
- Machine B
- Sensor A

**Post Processing**

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

**Data Analytics (Data Mining)**

- Meta-Data

**Data Preprocessing**

**Function**

- Data Classification
- Data of Data (meta-data)

**Required Standards and Technology**

- Model Classification
- Model Tuning and validation
- Problem Classification
- Problem Commonalities
- Machine Learning/Training

We need standards and protocols.
Predictive Analytics Workflow

- Standardize the predictive models
  - Model definition
  - Model Composition
  - Model chaining

Standards and protocols for this information flow:

1. Standardize the predictive models
2. Model definition
3. Model Composition
4. Model chaining

Standards and protocols at the same time:

- Interface Standard
- Protocol Standard
- Ensure compatibility

Data visualization

Prediction

Decision Storage/Decision Processing

Raw inputs

Outliers, missing values, invalid values

Normalize, Discretize, Filter etc.

Scaling, Decision, Scores etc.

Standards and protocols define both the transmitter and receiver function at the same time.
Big Data Analytics Solution

Application Layer

CAPP, MES, FDC, YMS, …

Integration Layer

Model Life Cycle

Creation → Deployment → In-Use → Disposal

Life Cycle Control

Duration Control, Uncertainty Resolution

Analytics Modeling Layer

Statistics Approach

R, …

Machine Learning Approach

Neural Network, SVM, Decision Tree, …

Big Data Infrastructure Layer

R Hive, Hadoop, HDFS, MapReduce, …

Data Layer

Static Data

Process Plan (STEP-NC), Production Plan, Master, …

Dynamic Data

Monitoring (MTConnect), Metrology, Defect, …

Shop Floor Layer

Manufacturing Process
Data Analytics – Past, Present and Future

Reduce the information overload. Can we get the same level of insights with less data?

<table>
<thead>
<tr>
<th>Data Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>Past</td>
</tr>
<tr>
<td>Relevant and Useful Data</td>
</tr>
</tbody>
</table>

Current DA

Big Data

Reduce the information overload. Can we get the same level of insights with less data?
Standards
SDOs and Industry Consortia

• Standards activities (good vehicle for industry interactions)
  – ASME
  – ASTM
  – IEEE

• OMG, MESA, ISA, MTConnect, AMT, AIAG
• OAGi, SME, ASME, DMG
• Exploring OPC Foundation, AutomationML
POTENTIAL COLLABORATION

• Industry Use case modeling
  – Reference architecture, performance metrics and assurance, modeling methodology, and big data analytics

• Standards for smart manufacturing – use cases
  – Verification and validation
  – Data driven models and uncertainty quantification
  – Participating in standards development activities (OAGi, OMG, DMG, ASTM E60.13, ASME V&V, MTConnect, MESA)

• Research collaboration
  – With our academic partners
Acknowledgements

- Members of SMSDA Program