Data Science Applications in Manufacturing

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About Me

Education
B.E in Information Science and Engineering, 2013
   Acharya Institute of Technology, India
M.S & Ph.D. in Industrial Engineering, 2019
   Western Michigan University, MI, USA

Work Experience
● Data Scientist 3, NAPIC, DENSO 2019-Present
● Data Scientist, DENSO 2017-2019
● Undergrad & Grad Course Instructor, WMU 2017-2018
● I.T Tech, ETS, MI 2016-2017

Other Stuff
Number of Research Publications 8
Journal Reviewer 3
Number of R-Packages 4
Number of Unpublished Work 4
Number of Patents 1

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Everything around you is “manufactured” and has gone through extensive and complicated “supply chains” to get there.
- Manufacturing contributes to 16% of global GDP (14 trillion USD) [1]
- India’s national manufacturing policy, adopted in Nov 2011, call for setting up national manufacturing zones, creating 100 million manufacturing jobs, and raising manufacturing contribution to GDP from 16 percent to 25 percent by 2022.
**Industrial Revolution**

**INDUSTRY 1.0**
- Mechanization, steam power, weaving loom

**INDUSTRY 2.0**
- Mass production, assembly line, electrical energy

**INDUSTRY 3.0**
- Automation, computers and electronics

**INDUSTRY 4.0**
- Cyber Physical Systems, internet of things, networks

1784 1870 1969 TODAY
Industry 4.0 refers to a new phase in the Industrial Revolution that focuses heavily on interconnectivity, automation, machine learning, and real-time data.
**Operations:** Machine programming and Machine connectivity

**Backend:** Database management and application integration

**Frontend:** Human Machine Interface development. Ex. web interfaces, augmented reality, wearable technology

**Cyber security:** Managing security policies on IoT devices
Data Science in Manufacturing
Why Data Science in Manufacturing?

- Data science in manufacturing has gained more prominence to achieve a simple goal of Just-in-Time (JIT).
- The goal of JIT is “Making the right products in right quantities at the right time.”
- One might ask why JIT is so important in manufacturing? The simple answer is to reduce the manufacturing cost and make products more affordable for everyone.
- Data science helps in providing deeper insights manufacturing operation, automating processes and reducing the variability.
Manufacturing Data Scientist Skill Set

MANUFACTURING EXPERTISE

DATA SCIENCE
- Statistical Research
- Data Processing

COMPUTER SCIENCE
- Machine Learning

MATHEMATICS

PRODUCTION

ENGINEERING
- Process, Quality, Safety, Lean and Logistics

MFG EXPERT
- MFG Tech

BUSINESS
- Products
- Sales, Customers, Budget, and Legal
Tools used by Data Scientists
Applications of Data Science in Manufacturing

- Predictive Maintenance
- Process Monitoring
- Process Quality Prediction
- AI Image Analytics
- Environment Monitoring
- NLP for Safety
- NLP for Maintenance
- Human Body Motion Analytics
- KPI Forecasting
- Product Price Quoting
- Weather forecasting
- Supply Chain Optimization
- Bottleneck Analysis
- and many more
Manufacturing Data

- An average automotive manufacturing plant with machine connectivity could generate over **100 TB of data each day**.
- Data is generated from images of parts, sound, sensor data, process data etc.
- Most of this data is usually preprocessed and aggregated before storing.

AOI  
Sensor Data  
Process Data
Applications of Data Science in Manufacturing
Cost of Machine Breakdown

- In 2014 the average downtime cost per hour was $164,000. By 2016, that statistic had exploded by 59% to $260,000 per hour. [1]

- In automotive industry, it’s estimated that 1 minute of downtime costs automotive manufacturers $22,000 per minute or $1.3 million per hour.

- Some estimates ran as high as $50,000 per minute. [2]

- A plant shutdown due to downtime could affect the supply chain and the downtime cost adds up throughout the supply chain.
Predictive Maintenance

Why Predictive Maintenance?

- Increase tool life
- Improved product quality
- “Zero” unplanned downtime
- Productivity from PdM > PM
- Process predictability

![Diagram showing ROI and different stages of maintenance](image)
Deep Learning based Vision Automated Optical Inspection (AOI)

- Traditional vision systems are good for measuring product location and dimensions
- **Need**: Human operators are used to measure any cosmetic defects or missing parts
- **Solution**: AI vision systems are used to measure the quality of the product (scuff marks, scratches etc) and "eliminate the need for human inspectors."

![Diagram of the process](image_url)
Predictive Quality

- SPC tools and procedures can help you monitor process behavior, discover issues in internal systems, and find solutions for production issues.

- **Problem:** SPC measures current product specs. It does not tell when the process deviates.

- **Solution:** Use ML tools with SPC to predict when the process deviates.

*Example*

Piston Rings → Machine → Measure diameter → Prediction Over Time
Product Price Quoting

- Product quoting for a manufactured product is very risky. In most cases, they are quoted based on previous work and expert knowledge.

- **Problem:** Highly customized product such as furniture and machines to build products are often quoted based on expert knowledge and guess work. Quotes are reviewed numerous times before delivery.

- **Solution:** Use statistical Models like linear regression to quote customized products with high degree of accuracy.

- **Application:** Steel Case a furniture manufacturer has been using similar technique for product quoting.
Challenges
Challenges

- **Lack of Subject Matter Expertise:** In manufacturing, knowing the manufacturing and process terminologies, rules and regulations, business understanding, components of supply chain and industrial engineering is very vital. Lack of SME would lead to tackling the wrong set of problems, eventually leading to failed projects and, more importantly, losing trust.

- **Reinventing the wheel:** Every problem in a manufacturing environment is new, and the stakeholders are different. Deploying a standard solution is risky and, more importantly, at some point it’s bound to fail. Every new problem has a part of the solution that is readily available, and the remaining has to be engineered. Engineering involves developing new ML model workflows and/ writing new ML packages for the simplest case and developing a new sensor or hardware in the most complex ones.
Conclusion
The Big Data Analytics in Manufacturing Industry Market was valued at USD 904.65 million in 2019 and is expected to reach USD 4.55 billion by 2025, at a CAGR of 30.9% over the forecast period 2020 - 2025.

TrendForce forecasts that the size of the global market for smart manufacturing solutions will surpass US$320 billion by 2020.

Return on Investment for every data science project is > $100,000. This is significantly higher than any other industry.

Cheaper IoT devices, cost of storage and cloud technologies are pushing the boundaries of analytics in manufacturing.

Data Science in Manufacturing is here to stay for a very long time.
Questions?