AI in Manufacturing

AN INSIDER VIEW

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Introduction

"The earth furnishes the means of wealth; but wealth itself cannot possibly have any existence, unless through industry and labor which modifies, divides, connects, and combines the various productions of the soil, so as to render them fit for consumption" - Adam Smith.

Stylisations in economic development of developed and more importantly developing nations highlight the pivotal role of manufacturing as an economic activity for economic prosperity. Manufacturing growth is directly linked to increasing wages and prosperity in societies. But not every economy has risen the prosperity ladder through manufacturing due to various reasons including trade barriers, lack of suitable infrastructure, automation replacing workers, rising costs and technological advancement among many. Developing economies manufactured goods at a competitive cost mainly due to labor arbitrage and after a period this arbitrage opportunity gets offset once wages start to rise or arbitrage margin reduces due to technological advancements that allows firms to produce more with less resources.

Among the many technological advancements, Automation through either simulated processes or machine intelligence has had a profound impact so much as to bring down manufacturing cost in developed economies. So it became imperative for all to adopt AI in manufacturing to remain competitive.

History & Importance of AI in Manufacturing

The inaugural use of AI in manufacturing can be traced to the 1970s, which saw the advent of discrete manufacturing using computer-assisted design (CAD) and computer numerical control (CNC) machines. Over the years, CAD and CNC incorporated advanced algorithms etc. to improve accuracy and optimize performance. By the 1980s and 1990s, manufacturers' focus shifted to systems and applications that capture data and provide high level insights. These inventions made real-time data collection and data transmission faster and easier while streamlining production through automation.

The advancements in automations have become the backbone of AI implementation. Automation technologies integrated with AI applications will help organizations to :

- Optimize operations and increase efficiency
- Predict machine failure and reduce machine downtime
- Reduce supply chain risks
- Predict sales volume for better capacity planning
- Improve the quality of products.

Advent of AI is eventually enabling organizations to monetize features such as predictive maintenance, real time monitoring in the form of service offerings or as quality assurance packages.
While the potential for AI in manufacturing is significant, actual adoption falls behind the hype due to various reasons such as

- Lack of good quality data
- Weak business case in terms of Return on Investment
- Challenging change management
- Lack of technical skills and competencies for sustained use of technology
- Focus on technology rather than Value
- Lack of proper digital strategy and governance for manufacturing

Despite the hurdles, organizations have started innovating for AI in manufacturing in a decentralized manner to avoid risks of investing too early into unproven use cases. So, at first organizations start with limited use (Proof of Concepts- POC) of AI technology in identified use cases without a clear vision. Upon successful completion of POCs, AI solutions are scaled, leading to wider adoption across value chain.

We have documented our experiences through AI implementation in use cases that demonstrate successful cost optimization. These cases serve as practical guidelines for achieving success and avoiding pitfalls when implementing AI solutions in manufacturing operations.

Use Case 1 - Predictive Quality

The initial use case we encountered as consultants for a manufacturing firm revolved around the combined objective of maximizing quality and optimizing resources.

Problem Statement:

A cement manufacturing firm wanted to improve their efficiency in terms of quality control and resource utilization in the manufacturing process. They were experiencing erratic quality control (due to hourly random -sampling for quality control), inefficient power consumption (which consists of ~20-30% of total cost) in manufacturing compared to their peers, and people driven quality control due to human judgment-based interventions. The core problem was a lack of awareness about the correct quality control intervention.

To address the challenge, we envisioned obtaining real-time insights into anticipated quality. We considered using machine parameters to guide corrective actions. As a solution, real-time data on the manufacturing process and operating parameters, driven by machine learning algorithm, were employed to predict output quality. The predicted quality served as a trigger for the automated quality control system, allowing it to implement corrective actions by managing manufacturing conditions and balancing processing time and intensity.

To monitor performance of the implemented solution, quality predictions were benchmarked with actual quality daily. Regular weekly huddles were conducted to ensure consistency in decision-making regarding changes in operating conditions. From IT side, end to end machine learning operation loop was set up for -

- Failure Prediction
- Corrective Action
- Performance Monitoring
- Deviation Analysis
- Re-Training of Models
- End to End Dashboarding

The practice of Machine Learning operations played a crucial role in proactively addressing issues, and incremental learnings facilitated adaptation to evolving manufacturing conditions and inputs.

What we Achieved out of this?

- Achieved stable and predictable output quality, resulting in reduced re-processing time.
- Realized a 30% reduction in power costs.
- Attained a 5% increase in throughput.

Things that stood out well for us:

- Emphasis on Machine Learning operations as a practice
- Utilization of in-house capabilities to enhance Return on Investment (ROI)
- Possession of a digitally proficient manufacturing team
- Establishment of a Project Governance Board post a successful Proof of Concept (POC)

What to look out for to succeed :
- Continuous monitoring of performance
- Continuous learning and adjustment, including re-training of models
- Customer centric approach to modeling

Use Case 2 : Golden Batch Analytics for a Life Sciences Company

In the second use case, we implemented an analytics solution to improve Batch Quality, which was critical for profitability and Quality compliance, for a Life Sciences Company. The batch with best output yield is called as Golden Batch.

Problem Statement:
The cost of deviations in batch quality can cost up to 5% of the revenue per batch depending on the nature of product. The sole method to analyze historical and time-series data for exploring batch deviations required experts to spend a significant amount of time manually reviewing batch data. Significant time was spent in Data extraction, visualization, and plotting to create process parameter profiles with the objective to reduce process variability and increasing yield. However, this manual approach became increasingly inadequate for precisely identifying relationships, batch process conditions, and batch output quality. The current method had two key issues:
- Golden batch profiles require many hours to be spent manually
- Three-way data (Batch Process Parameters, Batch Process Conditions and Batch Output Quality) makes it hard to optimize process inputs to manage batch yield

Action taken was two step approach
- Applying advanced analytics algorithms to identify Critical Process Parameters (CPP)
- Finding golden operating conditions of each CPP for maximum yield and conditions that of CPP that can cause Lower Yield.

Achievement
We increased yield and revenue with minimal or no added costs. Depending on the product, maintaining golden batch conditions can yield benefits of 5-10% of batch revenue. The impact was so profound that the Head of Manufacturing and CIO formed a joint team to implement the practice across the product portfolio because it helped immense potential during the economic downturn.
Companies hardly invest in new technology during severe economic downturn unless they are cash rich. But this investing approach was contrary to usual practice because
- Business case was in line with strategic long-term initiatives.
- Established process maturity and high level of digitization ensured good data quality.
- Digital First Culture and strong governance framework.

Strategic Framework for AI Adoption in Manufacturing

Leveraging our experience, we have developed a strategic framework to help stakeholders in assessing business cases and making informed decisions on AI investments. This framework plots use cases based on business value and complexity, facilitating strategic discussions for manufacturing stakeholders.

The framework features 4 quadrants based on proximity to business value and complexity axes:

High Reward Wins: These are “low hanging apples”. Organizations can prioritize this -

quadrant for its high ROI with low implementation complexity.

Strategic Initiatives: Use cases in this quadrant are typically strategic and long-term with high business value. However, the complexity of implementation is also high as these projects are executed over a span of 2-3 years.

Marginal Wins: These use cases offer minimal ROI, often occurring in nascent technology stages with high implementation costs. GenAI in manufacturing falls in this category for now, but it is expected to transition to High Reward Wins as technology matures and business outcome is well defined.

Exceptional Initiatives: These are short-lived initiatives typically tied to emergency situations, such as real-time monitoring of damaged equipment at a plant or in exceptional situations such as using robots in hazardous situations.

In mapping the use cases, stakeholders can consider parameters influencing business value and implementation complexity.

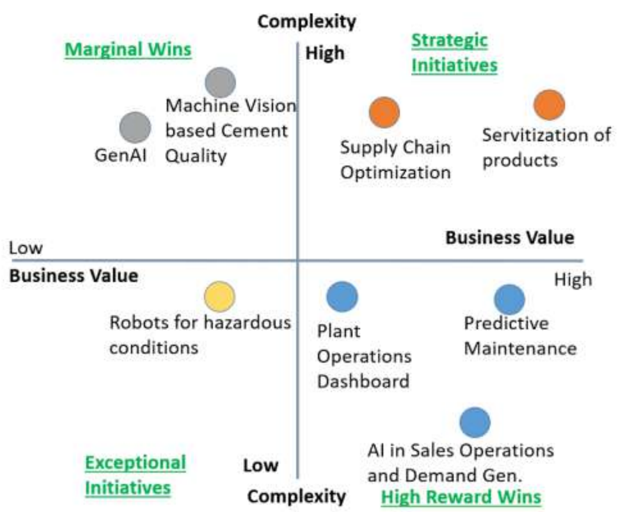
Business Value is often gauged using below parameters:

- Cost Optimization
- Revenue Maximization
- Risk Management
- Product Lifecycle Improvement

Complexity is determined by these parameters:

- Digital Readiness - IoTization of plants and systems
- Internal Readiness/In-House Capabilities - CIO Org. capabilities, Technology Infrastructure
- External Readiness - AI development partners, Supply chain dependencies

For successful AI adoption in manufacturing, stakeholders must prioritize the following



Organizations should emphasize on starting with a well-defined business case and establishing in-house capabilities for early success.

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