The Future of Manufacturing: LeanOverhead

"LeanOverhead can reduce Overhead and Labor Cost by 40%"

Michael L. George, Sr
Author of Lean Six-Sigma

www.leanoverhead.com

Patent Pending

LeanOverhead.com was not possible until AI LLM in 2024: The predecessor company was George Group Consulting

Google search on George Group Consulting (sold to Accenture)

Accenture acquired **George Group Consulting** to bolster its strategic process improvement and **Lean Six Sigma** capabilities.

Key Details of the Acquisition

- **Company Profile:** George Group was a Dallas-based boutique management consulting firm recognized for its expertise in **Lean Six Sigma** and process excellence.
- **Strategic Goal:** Accenture integrated the firm to expand its ability to help clients with "next-generation process re-engineering" and operational strategy.
- **Personnel:** Approximately **250 employees** from George Group transitioned to Accenture as part of the deal.
- **Notable Projects:** Following the merger, the combined team notably supported the **MRAP (Mine Resistant Ambush Protection)** vehicle program for the U.S. military, significantly increasing production output.

Integration into Accenture

The acquisition was part of a larger push by Accenture to dominate the **defense and government consulting** space.

- **Michael George**, the founder of George Group, is widely known for authoring several influential books on Lean Six Sigma.

THE ENVIRONMENT

"We have just concluded a very good meeting with the largest US Defense Manufacturers …They have agreed to Quadruple production"

Donald J Trump
Commander in Chief

"I think the AI Large Language Model is very exciting! Extensive, unique Bills of Material are the bane of Factories and Purchasing"

Lou Giuliano,
former President of ITT Defense,
and CEO of ITT Corp

"AI LLM is a powerful tool that must be used as a pre-condition to attain significant cost reduction in a Billion dollar company with tens of thousands of different part numbers. It is therefore likely that excess costs currently exist that can be eliminated by AI LLM."

Prof. Michael Hahsler
Computer Sciences, SMU

Mfg. Overhead Cost can be reduced 40% by LeanOverhead.com

LEAN OVERHEAD LEADERSHIP TEAM

Mike George, Sr.

Founder IPM, George Group and Founder

Author of best-selling books on Lean Six Sigma and AI

Wally Massenburg

Founding Partner

Vice Admiral, USN (Ret)
Architect and COO of the Naval Aviation Enterprise

Dan Blackwell

Founding Partner

Author LSS in the Age of Artificial Intelligence

Keith Johnson

Founding Partner

THE PROBLEM

- **Most Process Improvement focused on Labor**
- **Manufacturing Overhead>2.3*Labor Cost**
- **Manufacturing Overhead cost is lowered dramatically if the number of different Product Families is reduced per Fig 1. This achieves the Goal of Lean Overhead**

The Department of War (DoW) Requires Increased Manufacturing Capacity for All Weapon Systems

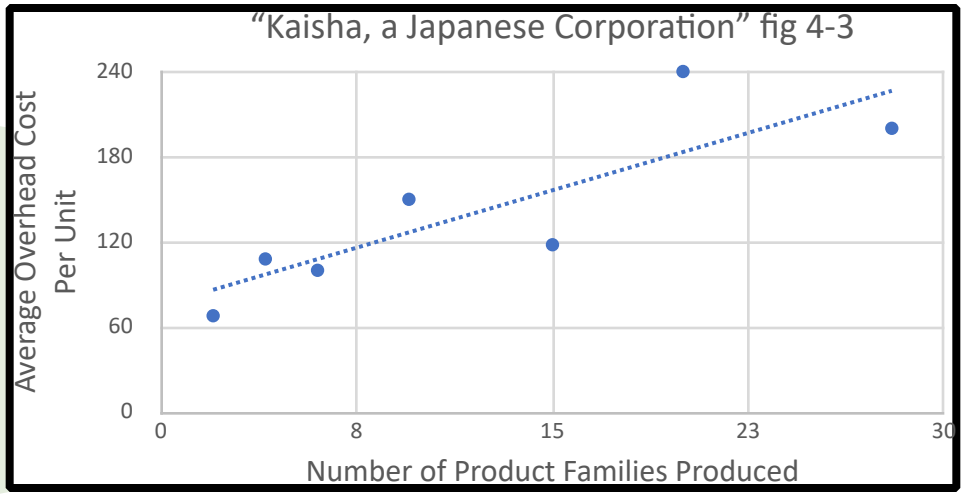


Fig 1: Overhead cost versus number of product families

American Manufacturing Can Be Strong Using Lean Overhead

CASE STUDY: THE POWER OF LEAN OVERHEAD REDUCTION

- International Power Machines (IPM) was not making profit, had high labor and manufacturing overhead costs, and hence was unable to grow in a growing market.
- Hypothesis: Data from the book "Kaisha" (Fig 1)proved that reduction of the number of Product Families would reduce manufacturing overhead costs by **~40%**.
- Implemented a pilot program to reduce the number of Product Families from 8 to 1. All sub-assemblies were made *mechanically identical but electrically different among the 8,* by eliminating 70% of components" which were "near miss" . Lean Overhead reduction increased revenue four-fold and Profit from zero to 20% of Revenue per Public Offering SEC S1 2-68681 available upon request or from SEC.

Lean Overhead dramatically Increases Production and Profit

INTERNATIONAL POWER MACHINES
Lean Overhead Reduction

How Lean Overhead Works

- **prior to availability of AI LLM in 2024**, all “near miss” vendor part numbers and internal fabrications were ***manually*** detected and identified to reduce families**.**

- Part number reduction of 70% was achieved by replacing all “near miss” parts with one part number. Example: each machine used 50 buss bars, of 5 different thicknesses, all 5 were replaced by the largest thickness
- Result: 8 separate families were reduced to one, cut overhead costs by **40%** due to the Lean Overhead

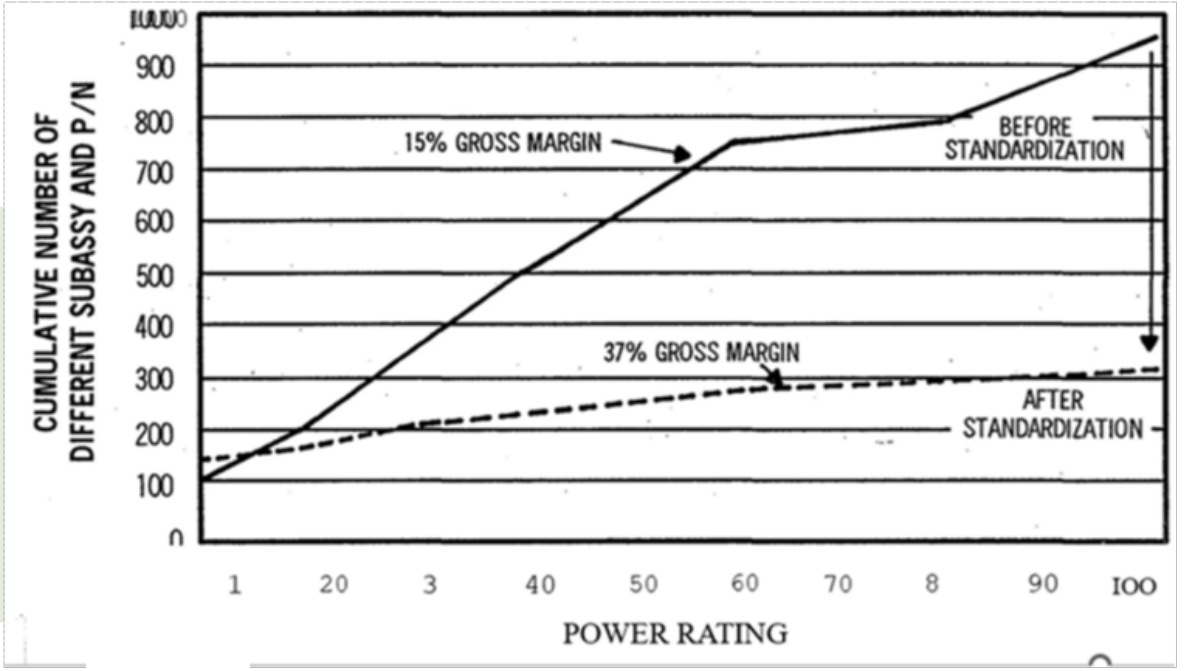
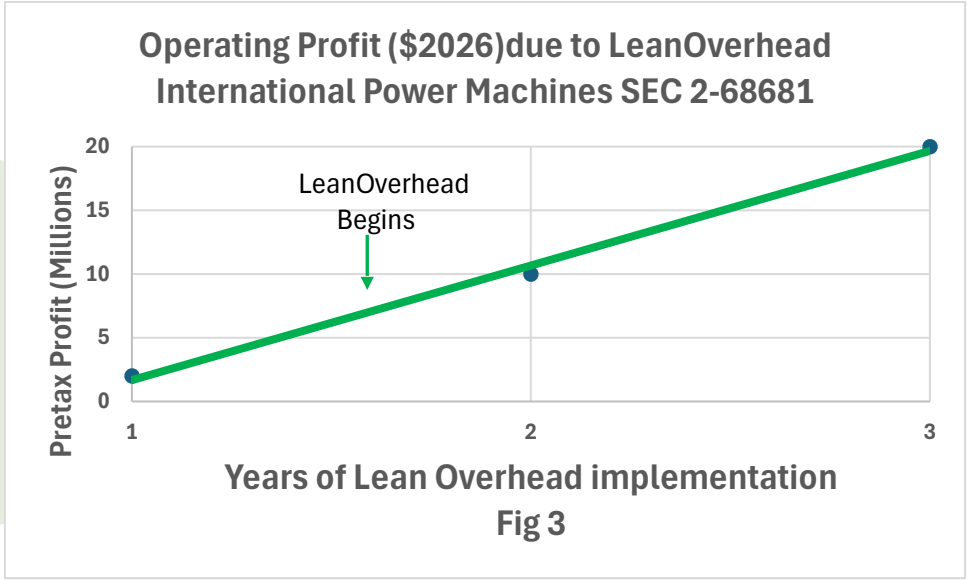


Fig.2 Graph courtesy of Prof. Jim Patel, Stanford Univ GSB

Overhead Reduction increased Gross Margin from 15% to 37%

LEAN OVERHEAD INCREASED PROFIT FROM 0% TO 20% OF REVENUE

- Over time, 8 different engineers had each designed one of the 8 families with no effort to eliminate “near miss” parts resulting in excess Overhead and Labor.
- All Sub-Assemblies were redesigned to be *mechanically* identical in the 1 product family
- Operating Profit increased to **20%** of Revenue (Fig 3)
- Lean Overhead increased Production **four- fold**
- Cut Manufacturing Overhead and Labor Costs **40%**
- Enabled a Public Offering: one measure of success!



Lean Overhead is the Future of Manufacturing

LEAN OVERHEAD REDUCTION IS THE KEY TO SUCCESS

- Manufacturing Overhead is Typically 2.3X Direct Labor in the Defense Industry
- In International Power Machine, inc., MFG overhead was reduced by 40%, see Figure 4.
- Lean Overhead due to redesign using AI LLM “near misses” will cut Overhead and Labor cost.
- Reduced number of product families from 8 to 1(Figure 4)

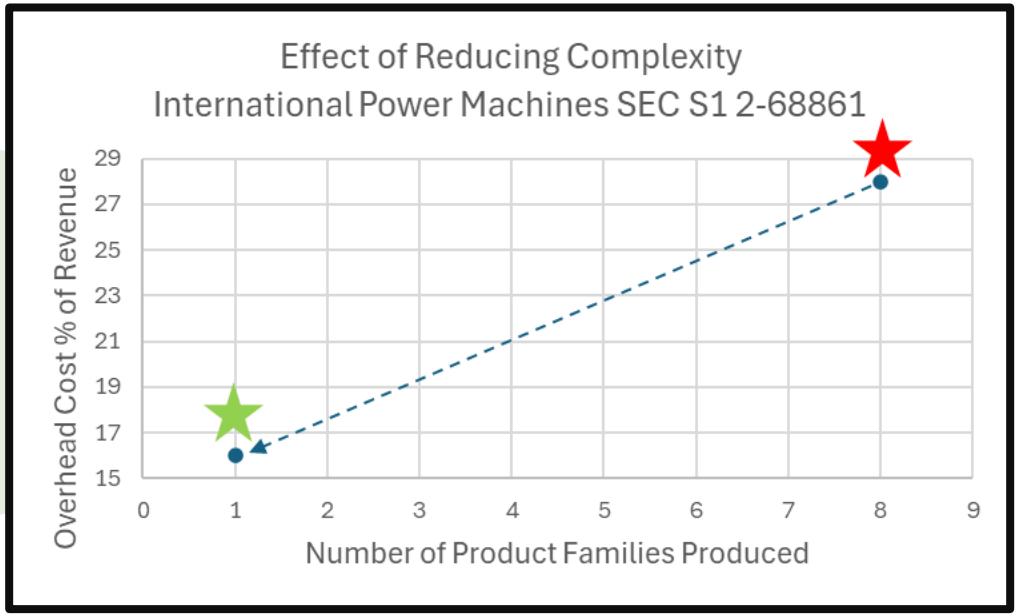


Fig 4. Overhead cost versus number of Families

Lean Overhead Reduction is Proven!

MANUFACTURING PRODUCTIVITY TRIPLES

- After reduction of “near misses”, all 8 products were *mechanically* identical
- Transformers installed in rear: size varied with power
- Increased power achieved by increasing internal DC voltage from 130 to 260 to 390VDC with common mechanical design.
- Assembly work instructions and wiring harnesses were identical: only electrical vendor components changed
- Largest profit improvement opportunity is Manufacturing Overhead followed by Direct Labor. Most Lean Six Sigma projects attack Direct Labor, not overhead

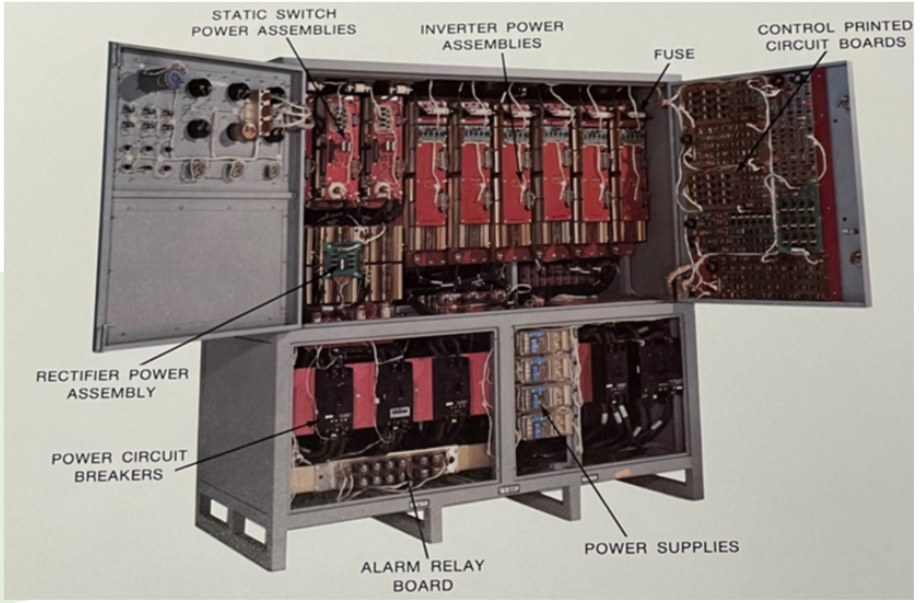


Fig 5.All sub-assemblies from 20kw to 160kw 60Hz, and 75kw 400Hz were redesigned to be *mechanically identical* reducing the number of families from **8** to **1**.

Lean Overhead manually Achieved Prior to AI LLM

THE AI LLM SOLUTION

- AI LLM can Detect and eliminate “Near Miss” Components from huge ERP database, eliminating slow and expensive manual methods: major reduction in Overhead cost
- Eliminates manual detection of “near miss” due to AI LLM “context” capability
- Manufacturing Overhead Costs reduced by ~40% due to less purchasing, stocking, kitting, QC etc.
- The majority of equipment Setups are eliminated reducing Direct Labor
- Labor costs further reduced due to mechanically identical sub- assemblies

Lean Overhead: The Future of Manufacturing!

REDUCING COST WITH AI LLM

"AI LLM can find both identical and near identical components by "fuzzy" searches dramatically reducing the number of purchased and fabricated parts, reducing labor and overhead costs.

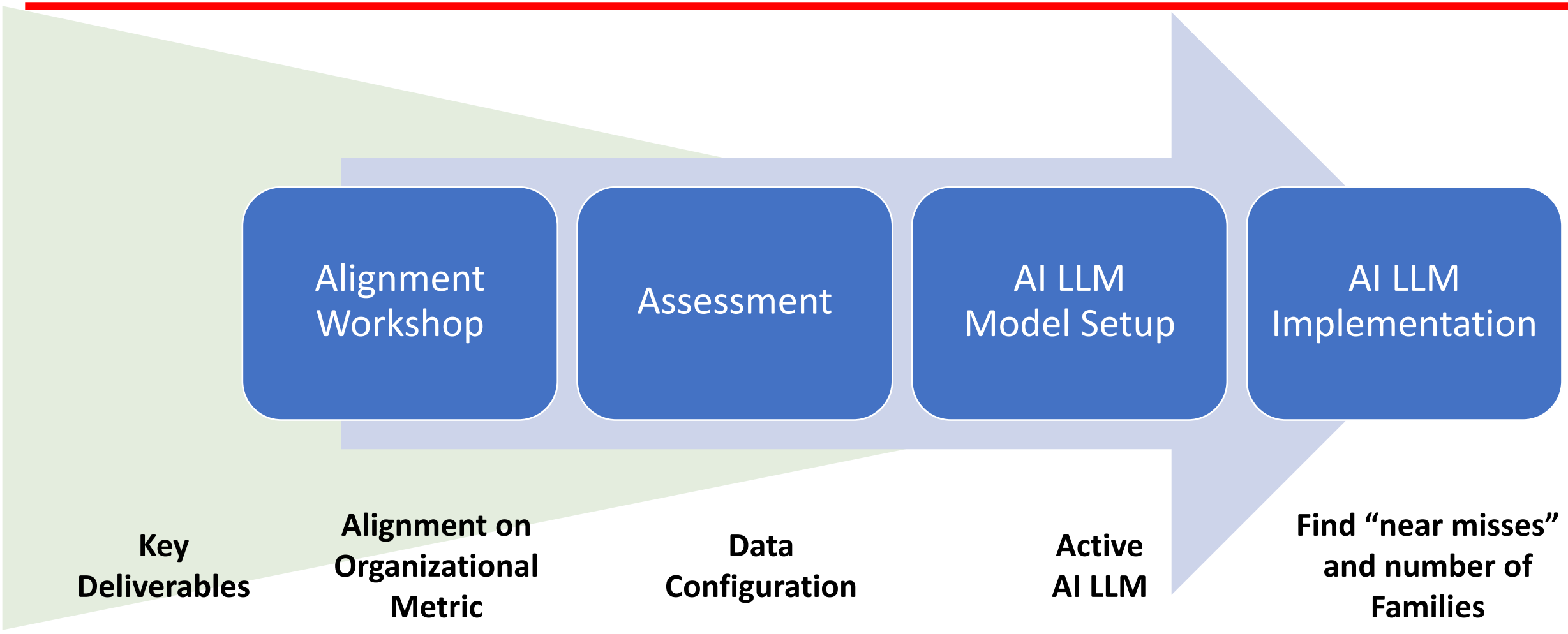
AI LLM then finds a small number of similar standard sub-systems or modules that can then replace the multiplicity of current subsystems with a much smaller number which are mechanically identical.

This allows the creation of standard Work Instructions with Photos allowing for a massive reduction in hidden Direct Labor Cost, and reduced Overhead cost related to Purchasing, Stockroom, Quality Control, Lab retest and other hidden costs."

Prof. Michael Hahsler, PhD

Dr Hahsler's Executive Overview of AI LLM applied to Manufacturing begins on page 15

IMPLEMENTING AI LLM



THE LEAN OVERHEAD PROCESS

Checklist for Improvement:

1. Which factory has the highest Mfg Ohd + Labor as % of Revenue? This is likely the best target for AI LLM
2. How many different families of products currently in the factory?
3. Initial Data needed:$Mfg Ohd and $Direct Labor cost, access to ERP database
4. AI LLM Identification of the % of “near miss” p/n in ERP
5. Estimate Reduction of numbers of Families and Overhead cost
6. Identify prototype projects for Manufacturing Engineering
7. Estimate of Profit Increase using 3, 4, 5 and 6
8. Build Lean Overhead team and execute

Lean Overhead: The Future of Manufacturing!

The Large Language Model applied to Lean Overhead

by Michael Hahsler, PhD University of Vienna, Associate Professor of Computer Science, Southern Methodist University

Large Language Models (LLMs) became available in 2023 from OpenAI, Google, Mistral AI, Cohere, etc. These AI LLMs can automatically extract part numbers, quantities and descriptions from ERP and translate into standardized formats like JSON (JavaScript Object Notation). JSON is a human-readable text format for data interchange, used to store and transmit data between a server and a web application. It was first specified in the early 2000s by Douglas Crockford. It is a widely compatible data format based on two structures: a collection of name-value pairs and an ordered list of values. Its simplicity makes it a de facto standard for APIs and diverse systems for communicating and processing data. (An API, or Application Programming Interface, is a set of rules and protocols that allows different software applications to communicate and interact with each other. It acts as an intermediary, defining how one application can request and receive data or functionality from another).

Key characteristics of JSON

Human-readable: JSON's syntax is compact and easy for humans to read and write.
Language-independent: While its name and syntax are derived from JavaScript, it is compatible with many modern programming languages, including Python, Java, and others.(Note: if you talk to 20 programmers, 19 use Python!)
Data types: Values in JSON can be one of the following data types:

- String (in double quotes)
- Number
- Boolean (true or false)
- null
- Array: An ordered list of values enclosed in square brackets ([]).
- Object**:** A collection of name-value pairs enclosed in curly braces ({}).

Common use: JSON is commonly used for transmitting data in APIs and is crucial for modern web development.

How JSON is used

Data exchange: It is used to send data between a client (like a web browser) and a server.
Configuration files: Many applications use JSON files to store configuration settings.
Databases: It is used in JSON document databases to store and manage operational data.
Logging: JSON is also used to format log entries, making them easier for both humans and machines to read and analyze.

LLM converts the two part numbers into two different tokens and then evaluate similarity in the embedding space. In the embedding space, these tokens may be very close together if they are often used in the training data in the same context (e.g., together with similar other parts). The tokens may also be dissimilar in the embedding space, if they have a completely different functionality and just share a very similar part number. Levenshtein distance cannot distinguish between these two cases because it does not use the context around the part number. LLM models that can be used to detect inconsistent parts or evaluate part similarity are typically from the **BERT (B**idirectional **E**ncoder **R**epresentations from **T**ransformer**)** model family introduced by Google researchers in 2018.

Part number Level: Thus we can now analyze inconsistent part numbers and descriptions reducing errors and duplicate parts as the pre-requisite to Complexity cost reduction. Inconsistent part numbers, which may be text-based, also fit into this category. We suggest you start with a proof-of-concept to demonstrate how LLMs reduce complexity and cost. Experienced consultants can assist your IT professionals in this process and in the selection of LLM software.

Subsystem Level: Thus far we have shown how LLM can find both identical and near identical components by “fuzzy” searches. The next step was to find a small number of similar standard sub-systems that can then replace the multiplicity of current subsystems. This allowed the creation of standard Work Instructions with Photos allowing for a massive reduction in hidden Direct Labor and Overhead cost. In this case ALL systems used a rectifier module to transform incoming AC power to DC power, used to recharge the battery and provide DC power to the Static Inverter modules which transformed the DC power (from either source, mains or battery) into AC power. All UPS systems had rectifier modules, inverter modules, control modules and associated power supplies. The question then is: can LLM

find, not only common components in the “fuzzy” sense, but also the common subsystems which are composed of the “fuzzy components”? The answer is **YES!**

Large Language Models (LLMs) can find similar subsystems, particularly when the subsystems can be described using natural language or have associated textual metadata. This capability relies on LLMs' ability to understand context, extract attributes, and compute semantic similarity.

How LLMs Facilitate Subsystem Similarity Analysis

Semantic Similarity: LLMs use embedding models to convert subsystem descriptions (e.g., functional requirements, technical specifications, design choices) into numerical vector representations. The "distance" between these vectors in the embedding space indicates their semantic similarity. Systems or subsystems with closer vectors are considered more similar in meaning or function.

Attribute Extraction: LLMs can parse technical documentation to automatically extract specific, structured attributes (e.g., performance parameters, material, function, interfaces). Comparing these extracted attributes allows for a more detailed, feature-based similarity analysis.

Reasoning and Context Understanding: LLMs can process a large amount of contextual information and perform complex reasoning tasks. This allows them to identify implicit similarities that might not be obvious from simple keyword matching, such as recognizing that "eco-friendly" and "sustainable" refer to similar concepts.

Conclusion: We can now identify

1. Common components using “fuzzy” analysis
2. Common subsystems below the total system
3. Final systems each of which is similar from an assembly and test perspective
4. Common work instructions yielding dramatic reduction in Labor and Overhead cost e.g. IPM,

Practical Applications and Methods

Model-Based Systems Engineering (MBSE): LLMs are being researched and fine-tuned to analyze requirements databases from past missions to identify semantically similar requirements for new designs, helping engineers reuse information and streamline the design process.

Product Matching: In commercial applications, LLMs are used to match similar products across different platforms by comparing descriptions and images, even when the descriptions are in different formats.

Automated System Integration: LLMs can analyze natural language inputs describing desired functionalities and suggest reusable service compositions or program code for integrating different software services.

Limitations and Considerations:

For high-confidence matches, methods like human curated lookup tables or specific algorithms

Performance in specific, complex domains can be improved by fine tuning models on domain-specific data or using techniques like Retrieval-Augmented Generation (RAG) to provide relevant context.

Conclusion: AI LLM is a powerful tool that *must* be used as a pre-condition to attain Lean Overhead in a billion dollar company with tens of thousands of different part numbers. Manual methods are impractical and hence are rarely used except when obvious. It is therefore likely that excess costs exist that can be eliminated by LLM.