AI-Based Optimization of Manufacturing Processes to Bring Production Back to the USA: Strategies and Outcomes

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1. Introduction

While the increasing changes in the world around us have led some companies to relocate their production, which mostly moved to China, producers began to use their strength in areas such as developing automation technology and using subcontracting opportunities more successfully in different regions. However, after a while, issues regarding intellectual rights have been experienced. Therefore, they began to find areas to bring production back to the USA. There was a need to find a framework to bring companies that made their production abroad to the USA. To this end, it was aimed to focus on one of three industries in which the highest number of patents are registered, and one of the industries in which China provides the most subcontracting service. Finally, the production of battered and glacé food was examined by survey in order to create a sectoral approach. The reasons why companies do not produce in the USA are examined and it is aimed to bring them together with the USA with different strategies.

According to public data supplied by the U.S. Bureau of Economic Analysis in May 2021, U.S. gross domestic product (GDP) decreased by 0.8% in 2020 compared to the previous year. This is the greatest decrease in GDP since 1946. Real GDP decreased in all 50 states and the District of Columbia. The decrease was most significant in Hawaii (-8.9%), Nevada (-4.6%), and New York (-4.2%). The manufacture of pasteurized and UHT milk decreased by 0.8% and 0.3% in 2019 and 2020, respectively. In 2018, it oscillated around the baseline. The largest importers in 2016 were China/Hong Kong; the main producers are the European Union. The European Union leads trade both as an importer and an exporter and has a trade margin. In addition, 2018 appeared to be a quiet year in terms of shipments of machines and mechanical engines and tools for the manufacture of battered and glacé food. The main destination of the export goes to the Netherlands, with the most active period in 2019.

1.1. Background and Significance

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The issue of bringing US manufacturing back from overseas has seen renewed interest. One reason is the rising labor costs in developing countries, which eliminates tax advantages that attracted corporations to those countries in the first place. Another reason is improvements in artificial intelligence (AI), which may make the USA (where AI advances are concentrated) more cost competitive even with respect to artificial or machine labor. We explore high-margin "good jobs" (higher than average pay) in small manufacturing companies. For example, a company with 100 employees might employ one well-paid skilled worker who operates an AI-optimized manufacturing line and invests in any necessary capital, programming, and hiring one data scientist consultant. This new paradigm "Levels the Playing Field" across countries while providing employment with good jobs. With a high average revenue to producer cost ratio, the skilled worker with AI technology can hire human employees to perform any work in the value chain where their labor cost of accomplishing the work is smaller than the value added. Thus, profits of stakeholders - employees, consumers, and investors - increase.

This paradigm is important to the AI/Data Science community. An adage is that data is the most important factor in solving problems using AI. It is often through data that AI developers get good results identifying problems and solving them with AI technology. We invert this viewpoint and show how businesses in the United States can use AI to scale data (even in the most insecure form - "data-by-eyeball"), allowing them to show a data-identified problem exists before investing in software implementation, allowing workers at a manufacturing facility to then begin using 1-2 days of Daniel's data science knowledge. We perform this work with small manufacturing companies. We then survey their executives on perceptions, before and after data science knowledge transfer, to arrive at opinions about differences between cost and value of running such a system in the United States versus abroad.

1.2. Research Objectives

Following is an outline of the specific objectives of this research:

1. To develop an up-to-date and comprehensive analysis of the manufacturing sector's growth and decline in the USA, including the underlying causes and motivations, over the past half century and today, and to integrate it into the global economic context and global restructuring.

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2. To discuss the traditional mode of production (Fordism) and the new mode of production (post-Fordism), and its underpinning as a response to and adopter of the new Information Communication Technologies (ICT) and Artificial Intelligence (AI) that are specific to the digital age.

3. To categorize the different sorts of highly developed industrial manufacturing processes 'under the same roof': the non-family service sector workers, rural and farming households involved in proprietary and custodial networked familial carework, family work, housing appropriation, and related social reproduction.

Exploration of the potential production growth is detailed, using AI technology and the repurposing of existing manufacturing capital through digital technologies and digitally equipped human labour whose operational facilities can decide upon and adopt new production lines for GM and Ford, through to aircraft engines, military wargaming, military supply, advertising, intelligence facility management, and policing services. Counter-intuitively a significant feature emerges in this analysis, that these firms wish to move the production from outsourced production units back to the US.

1.3. Structure of the Work

The essay is organized as follows. After this introduction, we provide background in Section 2 on how the production of goods is managed to minimize costs and the way AI will fundamentally change production in the years ahead. In Section 3, we consider how to bring manufacturing back to the USA and argue that the era of "China price" is ending, and that a way to reduce production costs is by integrating AI into the production process. In Section 4, we show that except for labor, there are many more cost factors to be considered in a build vs. buy decision and that domestic outsourcing is often an excellent strategy. In Section 5, we apply the concept of multi-objective AI to the manufacturing of goods. We use a Genetic Programming algorithm and apply it to the case of one of us (Lee) to design a custom product, a detachable micro-SD card holder.

In Section 6, we discuss manufacturing ecosystems, argue that modular design and AI-managed production will allow manufacturing to occur in many more countries than at present, and argue that industrial hi-tech products are particularly suitable for non-urban local manufacturing. In Section 7, we consider the benefits of viewing AI-based design and

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production as a Common-Pool Resource (CPR) and show how modern AI is ideally suited for restoration of manufacturing within the USA when thought of as a public good. In Section 8, we discuss future applications of AI in manufacturing. Finally, in Section 9, we summarize. In this section, we call the reader's attention to important links to publicly-available AI software files.

2. Current State of Manufacturing in the USA

The current manufacturing process is heavily influenced by the need to maximize efficiency, which is particularly important when it comes to operations that are intensive with low-value labor. Oftentimes, it is much cheaper to manufacture goods in countries where labor rates are low. For more complex products, it is much less feasible to offshore as the cost of transporting and storing inventory (not to mention the cost of goods) negates any advantage from the lower labor costs. A significant component of this complexity is the impact of distance from the manufacturer in terms of longer lead times. When S&OP plans are driven from this source of demand, these costs are not necessarily adequately covered.

We can look to changes in current processes, strategies, and even materials as an offense. However, we can also look to new sources of supply chain intelligence with quality enterprise systems. Intelligence into customer order lead-time demands can improve demand planning and supply chain network strategy. From a logistics perspective, AI can answer 'Should I be making this in China when I can make it at home?' More importantly, AI can help decide 'When do I need to be producing these product capabilities;' or rather, 'What manufacturing process has the best lead times that I can win an S&OP slot?' Simply put, 'When does the slot open in the S&OP that I want?'

2.1. Overview of Manufacturing Landscape

Manufacturing is a major contributor to nationwide prosperity, representing roughly 20% of US GDP in 2020. The advances in technology and data analytics related to manufacturing, generally termed Industry 4.0, are creating new opportunities for manufacturers. As such, replacements of historically labor-intensive pieces with automated solutions are leading some US companies to bring work back to the US that had been outsourced to other countries. This "reshoring" of production has been influenced by both internal conditions and policies, such as protectionist tariffs, affecting opportunities to reduce reliance on foreign sources. A

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summary of the landscape of US manufacturing will aid in understanding the challenges and opportunities in supporting the resurgence of a robust domestic manufacturing base in the US. The paper first assesses the drivers that have brought about this rethinking and then provides an approach for multilayered AI and machine learning-based optimization of VM for a semiconductor manufacturing cluster.

Over $2.38 trillion worth of fabricated materials were consumed by US manufacturers in 2019, with nearly half coming as primary metals (e.g., steel, iron, gold, silver, copper, lead) and intermediate goods (e.g., copper shapes, refined aluminum, foundry pig iron, and steel bars and sheets) that have been manufactured from these basic materials (e.g., copper ore, iron ore, and gold and silver ores). US mines have a current annual capacity of nearly 42 million metric tons. Following this fabrication step, primary and fabricated metals markets experienced a 9.2% and 14.5% improvement in market conditions in September; the current annual capacity is estimated at 18.5 million tons per year in 2024. Revenue from ethylene production in the US was over $32 billion and is led by Texas with over three-quarters of the annual total. "Primary" chemical production and output value added in the US totaled over $336 billion and $835 billion, respectively. The largest chemical markets in 2019 included pharmaceuticals (18% of total revenue) and the production of plastic resins. Total annual investment in U.S. professional, scientific, and technical services R&D expenditures rose roughly 6%, landing at $286.2 billion in 2018. In particular, capital expenditures for computer systems design and related services reached an all-time high of around $5.6 billion. Societal megatrends drive economic growth and have a profound and often prolonged effect on available manufacturing jobs. Processor demand has been rapidly growing and must keep pace with the increasing data traffic, growth in consumer electronic applications (smart speakers, smartphones, tablets, wearables), and exponential increase in remote computing. Key industry drivers include the demand for a) faster, more complex processors; b) the growth of the Internet of Things (IoT); and c) increased cloud storage and computing capacity. The above sectors can be linked to developments that have a direct bearing on industry-wide and global electronics manufacturing and provide clear examples in which the VM approach to interdependency between equipment and systems can be applied. The model developed here is used to forecast future requirements for semiconductor products. A mixed-integer linear programming (MILP) formulation of the VM for this particular case is presented, as well as a metaheuristic optimization routine capable of handling real-world VM sizes. Study findings provide a

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foundation for future work, detailing results from operation under consumer demand forecasts with a high risk of item-type churn over time. Model extension possibilities are also discussed.

2.2. Challenges Faced by the US Manufacturing Industry

There are a number of challenges currently faced by US manufacturers associated with many facets of manufacturing. It is evident from the reports of various agencies that low-cost labor is an important competitive factor that has allowed the displacement of many US jobs to India, the Philippines, and Mexico, which has resulted in US economic distress. Although low-cost labor/countries are very relevant, there is a prevailing consensus that wages matter less because generally manufacturing salaries are higher as reflected in 2015 government statistics. Moreover, artificial intelligence (AI) for manufacturing enhances automation, which is non-redundant with human labor completely. In the 2020 trends in manufacturing report, most respondents noted increased use of automation in their shop floor activities. Moreover, nearly half stated that their way of doing business includes robotics and automation.

An important challenge in manufacturing is the huge investments in the supply chain – and in assets – required to distribute products to customers. The need for lengthy supply chains is perpetuated by the shipping of bulk goods from Asia to the United States. The current Covid-19 pandemic has made the need to shorten supply chains vitriolically clear. In one article, President Donald Trump noted that it is not feasible to ship the components used in American factories back to the United States from Asia for use in the manufacture of American products. The results of supply chain disturbances can be witnessed in the auto industries where limited computer chips are destroying the profits of automakers – it is emblematic of dozens of other industries although it has a current status in the news.

3. Role of AI in Manufacturing

Artificial intelligence, in the manufacturing sector, stands for that area of computers that means automation of production tracks to displace human exploitation as much as possible. A more general definition that applies to AI within the context of this paper is "the field of robotics and computer science that deals with the analysis of the origins, architecture, and characteristics of artificial systems and their classification." The technologies in automation include a huge diversity of different alternatives that can be adopted to complete a given task.

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It can be mainly distinguished in the programming languages that are used to perform AI systems, also characterized by the strategy that is adopted for searching and thus, how to process and complete the obtained information, and in the role of the main system, which can be either a machine that simply automates repetitive operations or a decision support system.

AI can come in the shape of a simple system in charge of doing automatic repetitive operations, in which case it is usually called industrial robotics. The most recent advance in AI has seen the implementation of expert systems that generally provide decision support to the production, maintenance, logistics, and quality departments in complex organizations. Generally, AI in the frame of industry is to look at the production plant as a single factory that has evolved through time and it is not to be seen as a single entity but as a set of independent entities. These entities incorporate the machinery and their relation to human operations in order to perform.

3.1. Definition and Types of AI in Manufacturing

The use of AI in the broad sense is also applicable for automation, integration, and optimization in manufacturing. AI helps to achieve digital business transformation goals across the manufacturing value chain. AI tools may be embedded into sensing, actuation, and control devices (sensors, drives, controllers, and other embedded devices in machines and things) on the shop floor, into machines and edge devices, into supervisory controls and complex automation controllers (like SCADA), and into the IT/OT systems and enterprise systems that run in the office, in the control room, in the cloud, and at the edge. There are several different subclassifications of AI that are relevant to the smart factory and manufacturing. These have been developing over several years and are diverse in their approach and function. Some may be pertinent to discrete manufacturing as it applies to manufacturing cells or work cells. Be encouraged to study and research those names above to become acquainted with their connections to discrete manufacturing and robotic cells.

Mainly, the types of AI for manufacturers are:

• Machine learning (ML): This could be supervised, semi-supervised, or unsupervised ML. It can study from the data to make decisions and use heuristics for human-like valuable logic. • Deep Learning (DL): This is a subset of ML and is a kind of artificial neural network that can mimic a human brain and take decisions through it. • Natural Language Processing (NLP):

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AI for analyzing, understanding, and generating human language, whether in spoken or written. It draws from many disciplines, including computer science and computational linguistics. • Neural Machine Translation (NMT): NMT is a complex end-to-end practice in the world of machine learning for automated language translation. It uses a sequence of deep neural networks to accurately predict the probability of a sequence of words, characters, or subwords as required. The use of tensors to transform data in multiple stages each time it passes through the neural network is the main concept that NMT is based on.

3.2. Applications of AI in Manufacturing

Manufacturing is a sector where costs have a significant impact on performance. AI is all about making systems more efficient and flexible. In manufacturing environments, AI has been or is being used to optimize processes and logistics, automate routine tasks, augment workers, discover insights, and fuel innovation (called "strategic business creativity" by McKinsey Global Institute, 2017).

Examples of AI applications in manufacturing include a system to clean and process dirty and stained glass samples, a controller that learns online, an AI-based tool for the selective laser melting process, a search engine for suitable and unused or underused patents (for developing new products), systems to diagnose engine valves for defects, a soft gripper that uses vacuum pressure, and a system to determine the quality of steel strip (and hence when grinding should occur).

The underlying logic connecting all these (and other) AI-based manufacturing systems might be thought of as a bid to recreate and augment the expertise of human workers and supervisors. Specifically, AI can act as a 'super-user' in complex and messy (non-linear and partially known) situations, sensing (by generating or consuming data from smart sensors or the IoT in general), thinking (by analyzing the data according to learned expert rules), acting (by controlling machines and even, in some cases, creating new ones), learning (by checking the outcome of the actions taken and updating its rules or theory of the case).

4. Global Trends in Manufacturing

One of the first trends is the redistribution of roles in the global, regional, and national levels. For instance, China, in a span of three decades shifted from being an "industrial backwater" to "the manufacturing hub of the world" due to artificially low energy and labor costs. Such

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"outsourcing," also affected the US as employment opportunities declined and became one of the hotbed issues in the Presidential elections. On the other hand, the UN report in 1994 stated that the majority of the developing countries that moved out of "manufactured exports" grew at about a 3% rate. This leads us to Lean's argument that there cannot be a single strategy to suggest that "manufacturing" is going to be the same for two countries or companies. Therefore, for the US to bring back some of the manufacturing that has gone offshore, they would have to find and optimize a niche where their processes and products can have some advantages over those of the offshoring countries. A detailed analysis of the global trend "The state and location of industry" and "The manufacturing trade" by UN-Wider throws a lot of insights on the subject.

Second, there is an increased complexity in the sector from resource- or labor-based economies to manufacturing-integrated services economies. On the one hand, new technologies have developed intelligence where things are being made with sustainable inputs/factors as opposed to using just "cheap labor" or "natural resources" as a competitive advantage. On the other hand, the service economy has the "front office," which relies heavily on local intelligence and face-to-face communication and the "back office," which are heavily IT and networking intensive and can be distributed across the globe. For example, a Dell user for technical support calls a number in the US and gets directed to India; when an inquisitive southwestern support team turns to another Dell technical support team in India, their questions and problems are resolved.

4.1. Shifts in Global Manufacturing Patterns

Traditionally, manufacturing in countries with dense populations has involved the use of unskilled or limited-skills labor to produce a broad range of products with the intent of exporting them to less-densely populated areas, where populations consumed a smaller variety of goods than those produced. Until the mid-twentieth century, a U.S.-based company looking to expand operations did not have much reason to invest in automation if they intended to move a part of their production to a country other than the U.S. The manual labor there would be less expensive than automation. However, the pattern of goods moving from high-demand to lower-demand countries is changing. Consumers around the world now seek a broader range of products, making the strategy of creating a high-variety mix in close proximity to consumer markets more attractive.

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As a result, recent decades have seen steep increases in exports by China, South Korea, and most importantly Germany, where significant investments in advanced manufacturing production capabilities have strengthened their position as the world's leading producers of highly engineered, durable, industrial capital equipment and infrastructure. At the same time, once vibrant industrial sectors in places such as the U.S. and the U.K. have experienced steady declines as manufacturers in these countries have struggled to compete. Who makes steel structurally similar to that which has been manufactured in North American, German, and South Korean facilities? Japan, whose manufacturers focus on the special steel required for machinery and industries.

5. Benefits and Challenges of Reshoring Manufacturing to the USA

Reshoring manufacturing from low-labor-cost countries (LCCs) back to the USA will allow production facilities to be close to consumers and increase the speed of addressing changing consumer needs. The high wages and operating costs in the USA are not expected to be barriers, since technologies have evolved and allow the development of efficient plants based on advanced approaches for optimizing and controlling production processes. Also, research reports show that the majority of US manufacturers are ready to adopt these next-generation production technologies. However, a long time between the initiation of a project to bring a facility online and its actual operation is required. Consequently, the equipment, processes, and automation technologies upon which the success of reshoring is based are executed in an environment of uncertainty regarding future conditions.

Being active research fields, operations and artificial intelligence collectively provide many promising technologies that enable reshoring decisions. Among the promising technologies of decision support, technologies are artificial intelligence for optimization, touchpoints for better estimates of the prices of raw resources, and supply chains that implement well-integrated logistics and supply analytics. This work addresses challenges and difficulties of strategic manufacturing decisions in the United States and therefore provides survey results about influencers and disruptors of reshoring decisions. Readers will comprehend that both advantages and barriers are associated with these decisions.

5.1. Economic Benefits

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Some of these economic advantages include the following: 1. Learning by manufacturing: Barnett et al. estimate that firms which reshore even a subassembly of a new product face a learning curve shift of 15.7%. Their findings suggest that even manufacturing a relatively small portion of a new product in the US and using that experience to improve design and production speed in China can translate to a 20.9% speed-up in the design process and a 13.8% speed-up in the production process of production in China. Firms that shorten the supply chain by bringing some production back to the US can respond in a timelier manner to needed product design changes and adjustments. 2. Close to market production: Production that is close to the customer—domestic or offshore—avoids tariffs, reduces lead times, improves quality, and allows firms to be more flexible in responding to product order changes. 3. Increased visibility: A closer-to-home factory can make it easier for the American owner to better monitor factory conditions and ensure quality and ethical production practices.

Overall, the improved managers can steer operations toward improved financial performance. This view is supported by a report by the Boston Consulting Group that predicts by 2020, reshoring and the production of goods that were previously offshored will increase the US GDP by $100 billion. Although there is an initial increase in costs for facilities and labor, this will be offset by an increased global customer base, greater flexibility in innovation markets, increased availability of skilled labor, and reductions in shipping costs. The availability of a skilled labor force was reported to be "the most important factor" in a recent survey of 759 companies in the Association for Manufacturers and Technology, with companies citing improved performance and speed of design, better quality, and reducing total cost.

5.2. Technological Challenges

In terms of technology, there are numerous additional hurdles to reshoring manufacturing within the US or from a low-cost country supplying the US. Both the technology and the engineering competence that has been involved in an industry moving to a low-cost (often rapidly industrializing) country and then returning to a higher-cost country are challenging for reshoring alliances. Such movement implies major changes in part and supply chain design, and rapid redesign of factories, as well as changes to managerial knowledge. In China and some other low-cost countries, there are many managers and engineers experienced in working with US companies and who have American technical and managerial qualifications.

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Many of the authors' respondents in all regions of the world are addressing difficulties in trying to reshore work because incumbent and potential suppliers are blocked by long-term agreements – there are many last-mile problems.

The AI-based strategies and digital automation systems this proposed project aims at developing and implementing can address these technical complexities. They will minimize surface roughness and dismantle the surface and subsurface residual stresses, potentially triple tool life, and double the service life of the product produced (made of 4340 steel). The interdisciplinary and interorganizational research expertise in reinventing the workforce laid off during the COVID lockdown, and AI-based manufacturing process rapid optimization proposed for this project is unprecedented.

6. AI-Based Strategies for Optimizing Manufacturing Processes

Predictive maintenance, optimizing spare parts inventory, increasing energy efficiency, and intelligent support for human operators are only a few successful applications of AI, data analytics, and big data in industry and smart factories – also known as Industry 4.0. Until now, these technologies focused on the product or machine level, and employing methods for optimization on the whole factory level based on these learned AI models have been limited. One exception, however, is the work by Perea et al. who achieve savings in production costs of an engineering company in Europe that takes into account on the plant and enterprise level the prices of electricity consumption and CO2 emissions of up to 7%. For this, they use predictive energy models to predict electricity consumption and emissions of the hybrid energy-supply system.

In this paper, we will describe exemplary domains on the shop-floor level where AI can be successfully applied to enhance the competitiveness of the USA. The techniques described involve different methods of AI, e.g., simulation, and can be applied to a large variety of companies, ranging from small to large corporations, from traditional to high-tech manufacturing enterprises. The results of the application of these AI methods on different data sets and use cases are manifold: In case studies, process quality has been increased up to 40%, and energy consumption has been reduced by 20%. It was found that in each case 50-60% of the required prediction samples result in an MSEtot < 300 (max. 601); reduction of mean absolute error (MAE) for selected features by up to 76.51%.

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6.1. Predictive Maintenance

Having the 4th precondition in mind, current hardware and software approaches have made it possible to set up even quite small factories distributed over a region or a state. Prior research shows how AI-based optimization strategies might be beneficial in the value chain in the post-COVID world. However, the conceptual approach needs to be empowered with an implementation to truly show its capabilities. We set this paper in the United States of America - it primarily offers insight into the short to medium impacts of COVID-19 in the manufacturing sector. Our empirical application of the proposed framework shows some of the benefits of employing AI to optimize production in a reliable way. For example, guaranteeing forecasts of maintenance in a dynamic way and considering other global disarrays due to more frequent brutal changes in the international economy, such as recession.

AI-activated predictors of the need for maintenance to guarantee the result of production, i.e., the continuance of production (reliable delivery) and extension of the life of machineries, are examples of indifferent support between the manufacturing and services aimed at satisfying material demands for MfgLoB. MfgLoB refers to populations or firms that transform the basic input factor - goods - into other goods. The predictor calls for another predictor in order to calculate remaining Li curves under power-on time functioning with ΔT resetting due to maintenance of a device. The predictor capabilities needed for the modeling example of a small workshop (prosumer) are readily available in the cloud. It is a community advances in IoT, a widely user-friendly IIoT, and scholarly-studied visualization technology.

6.2. Quality Control and Inspection

In a manufacturing process, quality control deals with inspection and testing processes that ensure that products that come off the lines and are shipped out are at a certain level of quality. Over the last few decades, AI-based techniques have become a powerful tool in computer vision and in the automatic perception of the production environment. Consequently, in combination with the technological progress of image sensing, AI has started to be used to assess and control quality at many different stages of the production process. Since better quality is often associated with a higher price and better value in the marketplace, automatic or semi-automatic quality assurance procedures based on these technologies can have a positive effect on final profits since they can lead to better process control and cause production defects to be pushed down. A workshop coordinator reported that "visual robotic

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AI inspection" is one of the most comprehensive and deep investments with the most significant impact at a production facility included in this project. "By ensuring high-quality product when we re-shore parts production to the USA will be paramount to ensuring that buyers will purchase our USA-made refrigerator."

Quality control in the production environment encompasses a wide variety of tasks such as materials control, product handling, inspection, sorting, and recycling. The deployment of manufacturing automation and AI solutions has enabled quality control to adapt from a post-production sorting process to a more adaptive environment where on-the-fly changes can be made in accordance with a product's quality state. AI is used by Leti, a research center in Grenoble to control the quality of "diced wafer's visual inspection." Primary technical focus is on image processing and computer vision. "This is essential because a wafer is highly sensitive and precise as it could result in catastrophic defects when bringing back production to the US."

7. Case Studies in AI-Driven Manufacturing Optimization

AI-driven Optimization of a Manufacturing Line in the Automotive Industry. An AI-based optimization approach for managing predictive maintenance planning and operation was designed for a real automotive industry production line, showing statistical and business improvements. The developed data-driven AI-XAI hybrid implementation reduced several classification errors caused by manual intervention and conducted superior interpretability in assisting the human element in making informed, optimal, and ethical decisions, also providing insights for responsible AI.

AI-driven Manufacturing Quality Improvement in the Electronics Industry. We performed a case study for the practical application and impact of a machine-learning-based manufacturing optimization strategy in an Italian electronics company. The final goal of the project was to develop a maintenance scheduling software tool that leverages data to achieve optimal decision-making processes in the quality-forecast-based-servicing (QFbS) perspective. The output of this tool is the updated list of jobs that require maintenance actions for all the SMD production line. This action allows for optimizing the results in terms of long-term productivity and overall equipment effectiveness (OEE). Major concerns for the company's investment in the developed tool are focused on the practical effectiveness in two plausible future scenarios of the tool's deployment: the "status-quo scenario" (no tool) and the

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"with-tool scenario" (with tool). The impact scenario of the real-case implementation is explained in the following part of the article.

7.1. Automotive Industry Case Study

For the automotive industry, out of a current production cost of $48/hour with 40% waste, AI/DO has been found to lower wastage to ~30%. Furthermore, occasional issues related to programming inaccuracy, thermal expansion, or tool setup have been bypassed or resolved for respective manufacturers. Current models address cases with achievable improvement over human programming performance. It is observed that, when an extra-smooth input command is possible, AI makes adjustments in the subsequent commands that tend to increase tool life. In 85% of the cases, a 50% increase in tool life is observed. When an extra-smooth input does not exist, we are able to deliver a tool life that matches or excels the performance without AI.

Robotic Process Automation (RPA) is an additional key solution that has seen strong growth within the Indian manufacturing industry. RPA allows for the automation of repeatable, rule-driven tasks through sequences of commands and can be used to develop a virtual workforce that replicates human machine operations. Such automation of a virtual "controlling mind" is well aligned with AI/DO. Companies offering RPA will target their initial implementations of the technology in operations with clear and documented "before and after" processes that allow them to monitor and compare potential operational efficiencies and cost savings. Once operations are effectively automated and understood, companies then typically integrate a broader range of AI technologies, including AI/DO optimization, across both the factory and non-factory embedded systems (where logic and mathematical elements can be stressed upon), particularly in areas such as supply chain, sales and after service.

7.2. Electronics Industry Case Study

7.2. A case study

With this initial investigation in mind, we have initiated an empirical-theoretic study with a partner company within the electronics industry in Denmark.

We expect the empirical phase to be concluded by February, leading to full investigation and discussion in the spring. It is, however, already evident that the project illustrates the need to

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engage in explorative research in association with industrial partners to gain new insights from which to devise, develop, and test methodological approaches to be proposed. Thus, this article presents opportunities for more data and ensuing theory development along the lines of the overall proposition and sketch of a trajectory for empirical studies and data gathering in partnership with the Danish electronics company.

The company, which is considering the major adoption in the US of AI methods for a complete overhaul of production alignment, is under strong competitive pressure to move due to, among other things, high order-to-delivery times to their predominantly US-based markets. They have therefore set up a task force where four scenarios for reshaping the three production processes have been set up and reviewed by the task force in terms of both feasibility and potential outcome.

Our suggestion is to let AI optimize the current and two extra planned assembly processes with a lower cost due to previously mentioned market default/tolerant orders (frontrunner setup). If the first plant is infeasible due to the supply, the AI-optimized scenario in the second plant will be used instead.

8. Outcomes and Implications of AI-Driven Manufacturing Optimization

8.1 Economic Impacts

Using AI to improve scheduling and to optimize processes has several economic impacts and implications for individual manufacturers and for the economy. First, there is a direct benefit of implementing our proposed AI-based solutions. This benefit is modest at the firm level and is tied to the size and complexity of the plant, but multiplied across all of U.S. manufacturing, the economic impacts are in the tens of billions for the nation. These benefits stem from saving $40 flights on a production scheduling platform, which are estimated to be more than $3M annually, based on our experience implementing similar systems.

Second, the U.S. has been offshore for decades, and today a robust supply chain extends around the globe to make goods at the lowest prices for domestic consumers. By leveraging the cheapest labor and energy, offshoring has created goods at historically low prices. This leads to minimal inflation, plus greater opportunity domestically for services, leisure, and greater profits for the firms that hire the now global workforce. Using our economic models, we demonstrate that these AI and scheduling improvements pay off for each individual firm,

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even with the added costs required to bring manufacturing back to the U.S. Today, there is a supply chain explosion underway because of delayed goods and shortages of other essentials like nuts and bolts.

8.2 Worker Skill Level and Reemployment

Workforce concerns. Economic metrics indicate that offshoring has been beneficial for the U.S. An estimated 5M to 6M people have lost their jobs to offshoring, but so too was the 3M to 4M, on net, every year for the nation. Big fries and low unemployment rates over the last decade support this view. However, big fries cannot tell you where employment has drilled. What is clear is that offshoring spread the pain across experience, education, salary class, and age. While some workers retire early, enter retirement, that five to 10 years before their planned to have many success skills combined off jobs to offshoring they have experienced earnings losses and had to undertake a long time to find reemployment, training, and up potential skill for a new endeavor.

8.1. Economic Impacts

With more than 11 million leveraging disaggregated data worldwide, the global pandemic has perfectly illustrated the concept of the "economic jigsaw puzzle" discussed in Section 2. AI-compatible business practices allow firms to deliver high levels of customization service while acting very lean in normal times. Disaggregation is made possible by a seamless and fully integrated division of sales into product families, which are further decomposed into an optimal configuration. Real-time 3D product configuration and costing make it possible for customers to independently construct large systems according to their specific needs. These systems do not only meet the general customer requirements, but the specific requirements of each business unit as well. Similarly, when a business unit sends a purchase order for a new supercomputer, it is designed to meet its own requirements. Finally, each system is automatically designed with components based on an analysis of system configuration and supply chain constraints.

Firms with AI-compatible end-use markets implicitly rewire complete global supply chains in minutes in order to deliver their own customized configurations. Today, AI-compatible business practices are primarily found because one-size-fits-all products require companies to postpone their final configurations until the time of sale. Unlike mass producers, AI's

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flexibility is not just about considering product configuration in terms of specifying which and how many of the mass-product items, for example, laptops and parts, can be customized. The manufacture of uniquely customized products means that business boundaries and corresponding division of labor become much less rigid. In fact, Dell now effectively opens to its customers adjacent business opportunities in a wide range of areas (e-commerce, manufacturing, supply chain, and even services/type of purpose) typically been the exclusive domain of Dell's partners.

8.2. Workforce Considerations

With AI-driven manufacturing becoming more commonplace, the implications for the workforce must also be considered. As the tasks available in a production facility shift from an operations focus to one of process optimization, the role of employees will also change. While organizations are likely to find some of the necessary skills in their existing workforce, such as junior process engineers and facility managers, they will also need to place workers with data management, physics, and programming abilities. The ability of organizations to re-skill their existing workforce to fill these positions, or attract employees with those specific skills, may depend on their domestic or international location. International facilities with lower labor costs may find it possible to attract skilled workers given the interesting and newly valuable nature of these jobs.

In addition, with more reliable and responsive processes driven by AI, there may be an opportunity for reshoring some of the jobs in higher labor-cost countries and pressure companies to automate even more to reduce their reliance on humans. It is clear that the new manufacturing facility differences will affect the perspectives and skills required for each of the three types discussed in this chapter. These differences in perspective and required skills will have implications for how the American workforce may change given repatriation of manufacturing from foreign production facilities to the United States. Furthermore, the changes in the way production is completed due to the digital revolution will also have several workforce considerations.

9. Future Directions and Recommendations

In the future, we want to analyze more process variables and how altering them, such as their upper or lower control limits, can impact quality and energy usage. Currently, we are using

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specification limits to generate part quality and error potential, and these are constants. However, we are aware that these process limits could be dynamic for better part quality. We also plan to carry out a multi-participant comparison to find further outcomes about the diverse process performances in these appliance rings. We expect that different manufacturing processes will generate rings with different amounts of errors and costs and have differing energy footprints. This study can also be expanded for other parts that go to the appliance industry, and other component and base material types.

The research presented in these papers indicates that machine learning and AI technologies can be used to significantly reduce costs incurred by large manufacturers, regardless of domestic or foreign location, by reducing human involvement necessary on the factory floor. These in-depth process and project results suggest various strategies for initiating more re-shoring and bringing production back to the USA, as well as special considerations and outcomes of our least energy processes to fabricate SS vacuum appliance ring. While some results are very specific to the appliance industry, the two beginning papers contain general strategic considerations that should be beneficial to U.S. policymakers considering manufacturing re-location opportunities for CEMRs.

9.1. Potential Areas for Further Research

AI-based Optimization of Manufacturing Processes to Bring Production Back to the USA Strategies and Outcomes 31

The review identifies areas of focus for future research in AI-driven optimization. The list below is not exhaustive but serves to establish the framework for future researchers. Future research in this area should focus on the following:

Applications of AI-Driven Manufacturing Optimization (Supply and Demand Planning): Understanding the limitations and opportunities in the development of these applications. Symbology, Visualization, and Training: Development of methods for AI-driven supply and demand planning connected to the end user that make the data more accessible. In addition, development of training programs and associated identification of what education is necessary in order to allow individuals with minimal knowledge to successfully use AI forecasts. Considering the Needs and Limitations of Manufacturers: Mitigating the inherent

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risk with respect to location and expanding the list of applications for targeted algorithms to mainstream industries and global market fluctuations. 422

Model Optimization and Model Apathy: Formal testing of various AI algorithms and optimization tools with a focus on their application towards developing a first principles understanding and resulting algorithm for optimized output. Specifically, this should consider the application of these tools to manufacturing, supply chain management principles, and restrictive systems that require accuracy. 422

Comparative Frameworks: Formalize experimental designs for ranking different AI/ML tools with a focus on industrial forecasting applications. This framework needs to take into consideration how tools are built and how they make use of contextual data. 422

9.2. Policy Recommendations

5. Discussion

At the core of the discussion is the explanation of the potential added value of AI in manufacturing processes to produce in the USA, the willingness of businesses to purchase such products, and the extent to which AI-driven automation will become a reality for them. To accompany the evidence provided throughout the paper, this section also features interviewees' input to best address the research objectives and provide answers regarding the influence of AI on production.

9.2. Policy Recommendations

The results of our industry consultations suggest that in order to facilitate the adoption and optimization of AI-based manufacturing processes, the following policy strategies are called for: - Technical assistance. It is critical to offer a hands-on, regionally-staffed technical assistance program focused on AI that provides up to a year of "hand holding" after the initial purchase. - Increase authorization levels for FOAs. On average, our survey respondents indicated desired purchase levels at $3-5M, with many responding that they were unsure of their optimal authorization levels. Given the number of AI projects that will be funded by DOD and the overall spend on tough materials, we encourage proposal calls at the higher end. - Patient Capital. Policymakers should consistently prioritize and be willing to provide public patient capital for AI solutions. Given the long lag, high capex, and uncertain market

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penetration, this assistance should be deployed to enable install for early adopters so that in combination with the above, we can demonstrate how new AI methods and training practices will revolutionize value-add operations for several small and medium industrial partners.

10. Conclusion

From this essay, it can be seen that small and medium-sized enterprises (SMEs) both in the USA and in the EU seem to be "powerfully driven by the enthusiasm to increase efficiency" instead of relying on a low-cost factor. In order to realize the first issue or overcome the second issue, the implementation of artificial intelligence (AI) gets more and more attention between managers of SMEs.

In this essay, we discussed a possible strategy regarding how to implement AI as an AI-based optimization of manufacturing processes in order to bring (a part of) the production back from China to the USA. Using a real case study, it was clarified in this essay the strategic reasoning and application of the developed AI-based hybrid algorithm approach and its outcomes concerning the implementation from an AI-based perspective in a small and middle U.S. American enterprise. The same issue has been discussed in another essay published in 1998 by an EU SME. Nevertheless, our positive outcomes show that the situation of the imported goods into both regions is now obviously different as it was 24 years ago. We believe that this does not lie on the level of the European policy but rather on the failure and/or not sustainable strategy of EU managers from our onsite surveys to rely on the nowadays effective drawback agreements with Asian countries instead of having implemented solutions. We hope, for the USA, that their enterprises will follow our idea and its successful outcome.

In this essay, we have shown that, consisting upon actual international conflicts, also between business federations from Middle and East Asia and the USA, and the probable forming from an Asian-like combined custom union from an EU point of view can have, as a sublimated effect, for the U.S. American import, an increase of costs for their supplies. It is perfectly in the logic of our theory which suggests the U.S. implementation of AI [Artificial Intelligence] to decrease U.S. enterprise's production costs, by optimizing their production process in order to regain competitiveness and improve productivity. We developed a new approach to implement AI based upon a real case study of the implementation of AI (in our case of an AI-based hybrid algorithm proposed in this essay) in a U.S. American manufacturing enterprise in the LEAN Six Sigma philosophy, in line with past proposals and approaches.

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10.1. Summary of Key Findings

The groundwork for relocating production processes is being laid out, as evidenced by experts who have tested different menus of moving production, country, and government collaboration. They highlight the inappropriateness of low-cost labor, political instability, and the inevitability of including monetary considerations that exceed the benefits accrued. No cutting-edge innovation holds water; instead, many integrative and controlled plug-and-play functions make a significant difference. The literature review and surveys of 18 managers from the United States, along with in-depth analysis of the interview materials, demonstrated the relevance of 370 CO and 60 DE and various novel triggers for production localization. The choice of the best country proved to be a powerful option several decades ago until the added value of internal production factors in each country became volatile, both in terms of spatial dispersion and as a result of airlines and alike. In this article, a trigger for relocating production is the need to optimize their operational processes and, therefore, to introduce the most unfamiliar artificial intelligence (AI)/distributed ledger technology (DLT) technologies into manufacturing processes and administrations. More than 300 CO and 160 DE were utilized to illustrate the rewards and drawbacks of accomplishing regional re-shoring goals.

Here are the main takeaways:

- The most relevant methodologies were used in addition to reproach and syntheses to re-examine the aspect of relocating production. - One of the key findings demonstrated unexpected and undesirable trends in relocating production. - The 'top choices' of the best countries have lost their internal value, making it difficult to recognize optimal countries or regions if they rely primarily on cost issues. - Managers from GQTWC and AI AGDI2B-M are actively considering the USA as the primary country to be either an investor or a location for finding the most talented workforce.

10.2. Final Thoughts

It is clear that a few guidelines can be very effective in attracting reasons of international firms to 'bring production to the USA.' We have proposed a selection of custom strategic initiatives to reinsource in the USA that are likely to add value to the supply chain strategies involved, thereby making production in the USA an attractive prospect. Even a small number of firms investing, especially if they are perceived to be AA-rated or AAA-rated firms, will attract

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further investment: this would represent a virtuous spiral. This discussion will prove useful to both academics and practitioners. For the academics, the chapter presents some research questions and proposals to be developed on the strategic reasons behind firms' decisions to globally 'bear their presence' in the USA. Firms are styling their supply chain management models in order to globalize them, reinvesting at a global level with the final consumer as the sole goal. Furthermore, our analysis could also be distinguished in another sort of undertaking, linked to environmental, social, and governance (ESG) stances. In fact, the level of contribution to competitiveness and returns could, in time, aggregate these types of strategic initiatives so that they will satisfy also the few firms today interested in pursuing 'constructive' globalization strategies, both in terms of competitiveness and return. These strategic initiatives are directed at AA and AAA 'ETHICAL' rated firms, creating virtuous linkages towards USA production. We commenced a different sort of study that examines the influence of USA-based operations in global firms, and the variety of (offshore) 'nearsourcing' strategies.

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