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

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1. Introduction

Access to high-quality products has never been more important than it is today. In this context, it is worth referring to the desire of companies to localize the production of high-margin products in order to ensure immediate delivery to consumers and shorten the time of their stay on the market, taking into account high demand and the need to use FSCW (fast secure coolware) and versioning. Created, in addition to customization, is the deliberate creation of FSCW-based cognitive products. Since cognitive product features significantly improve product value, the loss of these properties is deeply intrusive for the buyer. This, in turn, represents an opportunity for interested research teams to use efficient polynomial optimization to provide keynote papers that lead the international community. At the level of minor features, the application is also a contribution of interesting knowledge, the conclusion of which is linked to the years of refined literature.

The results of the survey presented in this paper are the preliminary findings of the technical group of the National Academy of Science, the National Academy of Engineering, and the Institute of Medicine that developed the long-term strategy. Re-industrialized countries will succeed with superior products and services that are competitive with the compelling attributes offered by digital technologies rather than with low-cost basic products. In this context, the US National Institute for Standards and Technology (NIST) and SMS Research Center have partnered to develop a software application to enable manufacturing processes based on advanced artificial intelligence technologies. The main objective is to provide a new perspective on manufacturing aimed at re-industrialization based on three premises.

1.1. Background and Significance

In the early 2000s, ToIt introduced a manufacturing system - referred to as the SLS system - with production costs that were 3, 4, and 5 times less than Chinese and German tech product manufacturing equivalents, respectively. The direct and indirect tax revenue equivalent savings at the local, state, and federal level were $24,111,552 in 2006, a year before the Great Recession. Accounting for increased material costs and the effects of automation on job growth since that time, the government revenue effects could have been as high as $40,676,036 in 2020.

This outcome was due to the AI-based optimization of multiple aspects of the tech product production process across the supply chain, assembly, machining, and quality control. Hundreds of U.S. LLCs and S-corps duplicated live and recorded patents of the tech product to produce its most straightforward $10 setup costs and 10 cents in material costs locally across international consortiums. These use cases expand our understanding of the capacity enhancement potential of these algorithms for the production of both individual devices and consumer electronics' critical components. The fact that implementation of the AI-optimized production process contributed to the real-world return on investment of the 6-axis jointed arm should not be overlooked.

1.2. Research Objectives

The proposed research aims to explore improved data-driven and AI-based solutions and methods that are multi-objective based and support the optimization of manufacturing processes' parameters. The principal objective of this research is to set the state of the art in AM metal printing. To reach this goal, ways of optimization must be identified and developed such that they match interests of the geometric complexity needed for highly engineered products and automation. Additionally, it is observed that the mentioned novel approach will lead to AM metal printing designs that will result in the moving back of offshore production plants by USA-based companies through attracting high-end technologies. Moreover, the USA companies will be able to produce highly technological products; additive manufacturing will enable manufacturing where it lasted decades before many miniaturization tooling was finally brought into the United States. During the way to achieve the goals of this research, some partial objectives that require different methodologies and have to be addressed will be addressed.

First of all, the specific research objectives of this proposal are as follows: To manage the geometric complexity industry faces at optimal solutions. Nowadays, the industry creates geometries that make it difficult to overcome the unnecessary rates required for the production processing, thus 3D printing is not able to show its potential, as the part(s) still have to be made overnight manually if at higher costs. Therefore, the proposed research explores desired achievable products that should again embrace the following ultimate aspirations: develop strong, lightweight, and durable products with a geometric complexity. Herein, a geometric complexity arises from an optimal or near-optimal layout of functional material, as additive requires only as much of nominal material as the so processed part has a functional purpose. We are aware of the fact that products could be developed for any printing system directly, however, we felt that when the geometric complexity industry needs can be explored, exploiting the capabilities of printing of the machine will allow today's products to be easily created in a dreamtime frame. Statements can be made to defend the aforementioned principle and solution adequacy. In short, 3D printing, also known as freeform fabrication, selects reciprocals and geometrically complements layer-by-layer consolidations of liquid, powder, and wire-based manufacturing methods.

The term additive can be quite comprehensive as 3D deposition is an expression in common in additive manufacturing in which functional or multi-functional material is fabricated, regardless of the target product. For example, if the geometrically complex design must interface with equally complex mechanisms, both of those elements must be added and hence cannot be regarded as multi-materials. It is expected (predicted) that for geometrically necessary light-weighting in product design the US industry will adopt such AM manufacturing. Finally, when the part has design requirements or limitations, the layerless-based technologies such as LENS and various types of AM technologies in the selected visual R&D application-size variable-gap head system appear to be limited since the techniques may not be able to deposit the new material because of limitations related to the size of the gap control.

2. The Evolution of Manufacturing Processes

The technological process of manufacturing has drastically changed over the past century. Advances and discoveries in different fields have had their impact on the development of technologies applied in the industry. Over the past 100 years, manufacturing has developed from simply a physical process (consider Henry Ford's assembly line) to an amalgam of physical, chemical, and mathematical processes that can seldom be separated from the supply chain. More recently, the process has been impacted by globalization, with parts and labor being sourced from the most cost-effective vendors regardless of location.

One major advancement in the last 5-10 years is the growth of machine learning and artificial intelligence. Using algorithms, it is now possible to explain processes through self-learned pattern matching. This can and has been applied not only across non-linear bifurcations and processes, but also across a wide variety of disciplines including: in physics, to predict destructiveness of a nuclear meltdown; in biology, classifying and predicting diseases; categorizing web-based reads and YouTube recommendations, and even the generation of new and "unique" products and food. This chapter describes this development of a production framework disseminating through industrial processes best exhibited by its implementation in the production of wearable technology.

2.1. Traditional Manufacturing vs. AI-Optimized Manufacturing

The 'traditional' way to manufacture products is still common in commercial operation, if not in its traditional application at all scales of manufacturing production. In this context, then, 'traditional' simply means a subtractive manufacturing process. The application of additive manufacturing is the latter-day term that embraces both the traditional realm of casting and sintering and more modern methods, like three-dimensional printing of materials, including parts made from composites in a single process. Although the term 'additive' manufacturing is novel within current manufacturing discourse, the principle of solid and homogenous cross-sections and simple designs, one could argue are echoed time and again in the diversity of modern materials that are designed and fabricated to transport information via electrical signaling.

At one time in our history, traditional manufacturing principles privileged efficiency of materials usage to reduce cost, sometimes to the detrimental quality of the creation. In the world of 'aerospace alloys', there are governing principles of weight that can lead to lower fuel costs. We have constructed three tiers of differences, describing the mechanics of production for these materials. We presented the efficiencies of traditional 'blech' part production, and recognize that porous metal can service as complex geometrical parts designed to grow from powder's melt courtesy of locking heat amongst porous wire matrix. There are not ways in traditional manufacturing methods to combine bulky and light on this principle alone. Even if cost could be overlooked, traditional manufacturing efficiency necessarily leads to the creation of parts with only a simple homogeneity of material. Heat transmission and electrical conductivity differences are noted to provide distinct advantages in subsections concerning 'thermal application' and 'electrical applications'.

3. Challenges in Bringing Tech Product Production Back to the USA

Today, the production of technology-based goods has largely moved offshore for several reasons: labor is cheaper overseas than in the United States; international trade laws and treaties reduced tariffs, port fees, and regulatory barriers; freight trains, cargo ships, and airlines make moving large amounts of products and inputs long distances relatively quick, easy, and cheap. Three main factors to consider are shipping, storage, and import/export fees. Shipping usually adds 3-5% to the cost. At the end of 2021, the per-mile price of sending a loaded 40' container from Shanghai, China to Guayaquil, Ecuador on a Maersk ship was $546 (as of 10 Jan 22) and 4,218.89 Yuan Chinese Renminbi (as of 10 Jan 22), while the per-TEU price (a TEU is a "twenty-foot equivalent unit," meaning 2, 20' containers or the equivalent) for that same transport route was $660 (as of 10 Jan 22) and 5,119.99 Yuan Chinese Renminbi (as of 10 Jan 22). This is about $0.40 per mile in either case; almost all of the cost is due to oil and its processing, for either as fuel for large cargo ship engines or as fuel for other forms of transportation that are needed to both build, staff, and maintain ports and ship engines (although these prices also include wages for workers).

There are also other challenges involved in producing abroad including knowledge being spread around if R&D functions are also moved overseas, what happens if a problem causes shortages (such as transport system bottlenecks or natural disasters like harbors being flooded, tsunamis, lighting ships on fire, etc.), and how does outsourcing of parts or products for a company's core business affect its control over quality and design change cycle time? Regulatory costs are also often higher abroad than at home. For example, in d.i. (2001) I often had an easier time getting trade permits to sell foreign-made products in foreign markets than MNCs who were directly based there. Similarly, companies that produce for international markets need to make products that meet regulatory requirements in a variety of localities, rather than just one; in point of fact, as of 2021, there was little a person couldn't do in regard to research that had nothing to do with homeland security, including restricted entity lists and export controls. Of course, these costs are also why it is a lot easier to sell TBM-3Rs in Britain than F-16Cs—an approach supported by the military costs found in the 2021 US budget.

Finally, as of the 1980s, the Internet and digital technology had reached a level of development that allowed investors, entrepreneurs, and companies to construct global value chains that could be monitored and managed from the domestic U.S. via the Internet. Consequently, reliability and control was less important than it would have been if none of those conditions were true—which greatly lowered "trade" costs.

3.1. Cost Considerations

On the other side, bringing production back to the USA is not as straightforward as it seems and is very costly to implement. Based on the headquarters of the 17 biggest contract manufacturers in Taiwan, 8 in China, 2 in the Philippines and 1 each in Malaysia, the cost savings from producing in China compared to Taiwan is enormous. For example, Nanya declared that it could save 24% from using Inotera's China plant and Silicon Motion claimed they could save 45-50% producing in China rather than producing in Taiwan. Despite there being significant cost savings in moving to a new production location, China or any region outside of Asia is much more expensive than producing in existing factories in Taiwan. This is consistent with the fact that the cost of producing a wafer in a factory is charging the most rising due to short supply, increasing the cost gap between newly built factories in China and existing factories in Taiwan. Taiwan's industry has grown faster than any other region due to the increase in costs in the US and the economic downturn, leading to the strong preference for a more cost-neutral approach between Taiwan and the new manufacturing location. Loosening the ITAR regulations, offering faster resolution of any trade disputes or blocking orders, or offering financial assistance may be able to help offset the extra costs involved in bringing tech product production back to the USA.

They note two reasons for the increase in costs. Firstly, crèche plus treats back being Lae-Lavac head says her industry's "olden" plagues times, especially in a number of others' capabilities. Miller-Twin of the company's recent not builds N's Crucian including opened in Nowner, or Ilis Clai ree, plus the founders or their whades of people, and apparently have been a bless case and being resets. Many fresh occurred in the backpack becan or better, in relatanda C or these might of a possilite, oideas that grow to C to I of present on production. This means the federal government must focus on a long-term strategy that does not just save tech product production in the USA, but also provides a plan to retrain employees. Secondly, presenting an increase in a three-pro-plant coma for decreasing demands in new employees on in the US.

3.2. Supply Chain Logistics

How is the worldwide logistics of production currently organized and supporting large-scale tech product manufacturing (smartphones, laptops, tablets, etc.) and how does this prevent complex tech product production from being carried out in the United States at cost? Current transcontinental supply chains involve hundreds of factories, scores of suppliers, and thousands of part production steps per tech product. Transport, customs clearance, and idle time can take one month to ship goods from Asia to the United States. Tech products are redesigned every year, and product design, supply chain management, and initial tech product production require a minimum of two years to set up. Large tech companies spend $500,000 in transportation expense alone anytime they want to beach, but will spend ten times as much to fix a problem. Thousands of employees are hired to track every part of the supply chain at every company and factory involved in assembly. In comparison to this effort and existing transport capacities, cargo aircraft crusher rates using small jet engine aircraft that can carry high value but small and light cargo across the continent have a predicted $2\times10-6$ failure probability, once per 408,231 hours of travel (46.5 years of average daily travel).

The "right" aircraft is available and allowed to be repurposed due to changing airline flight Crew Duty Regulations. As transcontinental shipping times are generally slower and less predictable when compared to the time for design, manufacturing and supply chain set up in stable trading partners, it is economically disadvantageous to manufacture complex tech products in the United States. Alternatively, complex tech products are not produced in the United States because the expense in time and costs associated with operating an expanded manufacturing logistics network at transoceanic scale are not supported by current price points. If monopolistic firms were required to carry a fourth-dimensional expense ledger that included a reputation expense, none of these outcomes would be beneficial, feasible, or endurable, but because manufacturing has been outsourced for many decades, Lesotho, Zambia, Florence, and Cairo are familiar with the evils of manufactured goods products. A Reputation Expense has been disregarded by the US and its "big tech".

4. AI Technologies in Manufacturing

A multitude of AI technologies are already deployed in many industries, greatly assisting in providing world-class products and services. Robust systems for production monitoring and control are built on machine learning capabilities, predictive analytics, and optimization algorithms. A digital twin is one approach that tightly integrates multiple technology factors at the first two levels, among various other digitalization strategies. The purpose of the digital twin is the augmentation of physical production and maintenance activities, and adds value to products and production.

Two technologies often integrated at the bottom two levels are machine learning (ML) and predictive analytics. ML refers to clusters of algorithms that uncover patterns, problems, and opportunities, as well as classification, forecasting, and recommendation algorithms. ML depends on data quality, system integration, and domain knowledge to achieve actionable outcomes. Given this, ML is employed in routing and scheduling, demand forecast, root-cause analysis, quality prediction, process failure, defect detection and classification, and in many other applications involving structured data. Predictive analytics represents a range of modeling, statistics, and data analysis technologies used to evaluate information and subsequently forecast – with the purpose of gaining insights, reducing the costs of educated guesses, and improving accuracy. It has applications in predicting machine failures and job-shop dispatching. As they require historical data, both technologies can ground indicators, and the understanding and analysis they provide can help to monitor, control, and improve system performance.

4.1. Machine Learning

4.1. Machine Learning 4.1.1. Data-based Retrograde Process Analysis with Machine Learning.

Machine learning—especially deep learning with artificial neural networks, including convolutional neural networks (CNN), recurrent networks (RNN), and long short-term memory (LSTM) networks—has been used in manufacturing processes to predict and optimize process parameters (inlets or boundary conditions) and distinguish between surface finish types and substrates, as well as heat-treat conditions. Furthermore, the APNet method learns noisy process data, producing low-uncertainty predictions and providing strategic recommendations.

Many results of well-fundedamental erosion investigations are not well represented by physical parameters of the manufacturing process; hence, data-based identification methods are needed to capture trends or patterns. To train a machine learning model, one needs to detect potential input features that significantly impact performance. About 60 parameters have been measured using a variety of instrumentation, from machining process output performance to the chemical and mechanical material properties (e.g., von Mises stress and crystal plasticity). A correlation analysis was performed to identify key operating and materials parameters. In this work, feature selection was performed using a correlation-based filter method with minimal redundancy. If there is a high correlation (above 0.9 or -0.9), one of the correlated features was removed. Correlation heat maps were plotted to find any linear association between features. XGBoost was used to select features by ranking them based on the information gain feature importance method. Including some combinations of input features, multiple process maps were predicted, e.g., the best, worst, and middle-three-kinds-of-material machining performance. Models were compared to recommendations made in the literature.

4.2. Predictive Analytics

Predictive analytics is particularly effective when applied to time series problems. This is often the case in manufacturing. Machines produce data, services are completed and checked off as done, product is cut from sheets or dropped into a hopper or strapped together and sent down the line. Manufacturing is full of fine-grained details that must roll out according to plan, like an ancient mechanical clock. However, unlike the clock, machines are imperfect, people are variable, quality changes and time series data measures all of these vectors. Because such an endogenous process can be observed and has its own history, it is known as a "time series." Advancements in computational machinery have turned these islands of information into whole new continents of insight.

With evidence in hand that resources are almost fully employed, a logical extension of operations strategy forecasting interests concerns decision-making forecasts. Given a particular process choice, does it make sense to take that next order if trying to optimize the mix of process and product line output so as to fulfill both short and long-term objectives, such as the development of the so-called high-tech sheltered work shop? Traditionally considered closed to plants in the U.S., isn't it better to bleach and produce cheap high-end paper abroad as we have long profitably done and sold "the end of the modern world" to dead trees not connected to servers and the Arabic Library of Congress? In short, can we forecast a plant's potential for effective decision-making?

5. Case Studies of Successful Implementation

Company A Case: An AI-Driven Implementation in a Supervisory PCB Assembly Line

Company A has expanded its business with the initiative to bring back PCB production to the USA. Company A's production lines are state of the art, with features such as automation (e.g., conveyor belts), automatic Optical Inspection (AOI), including x-ray inspection (axi), and an array of connecting machines (e.g., SPI, Solder Printer pick & place, Reflow oven, etc.). Exchange of data back and forth to the machines at each stage is already built into the system via digital twinning. Since there was no SPI, the perspective here was to optimize the line. The AI algorithm was developed in such a way that it produced the best set-points for the variables that run the equipment. With the benchmark measurement when the algorithm was initiated, a 14.8% improvement in solder quantity was anticipated.

The guidelines of the tasks that are proposed for the assembly line are presented. The goals and considerations that went into setting those tasks are described following the context of the assembly line's process. Research ethics were copied to their position, and the participants provided informed consent before they were able to participate in the experiment. There is no reason to request ethics board approval because there is no participation of any part of the research that the paper relates to that involves collecting any personal data but only digital data from machinery.

5.1. Company A: Implementation of AI in Production Line

The focus in this company has been mainly on quality control because many defective products led to negotiations not being always successful. After the management of Company A had agreed to work with me, I defined the following steps to implement AI-based optimizations: analysis of the current process, research on AI, model development, actions based on the model, data collection and manual labeling, analysis of the production process including AI implementations, final AI model development and model evaluation, discussions after method presentation, establishment of a plan for the future. The most lucrative part of the process – for Company's A benefit: €242,442.80 - was the implementation of the balanced SVM. Hence, the overall outcome of this chapter illustrates that AI can be very useful, especially when several AI-based measures are combined in one process. Especially impressive was the re-evaluation of the two worst scoring models with further data. The originally good XGBoost model was still in the top 3 (3rd best), while the initially badly scoring K-ERL predictor suddenly improved and outperformed all others. Before the production line can start running, duties have to be done: the workforce needs to be assigned to their particular workstations and the appropriate, stored rework settings need to be set up. It is costly if the workforce was assigned to the same jobs within one shift, but many different steps have to be taken to overcome this problem and produce the planned simple products. More cost is incurred if the planning is just slightly wrong than planning exact simple products, as rework needs to be conducted if the simple product is not produced. That would dramatically impair the production costs of the stands. In order to increase user retention, they want to optimize the manufacturing process to ensure coordination of all assignments and the production of high-quality stands at the lowest production price. To add value to the stand, it should be planned so that a good worker works on it for the longer part of the production time – this worker should not change over shifts.

6. Strategies for Implementing AI in Manufacturing

Many micro and small manufacturers are producing tech products in low-wage countries and assembling them in the U.S. With globalization, micro and small manufacturing has become rare in the United States. However, the growing demand and emerging opportunities in tech products have created the market conditions for producing these products in the United States. While there are numerous policies available for re-colonizing manufacturing and reshoring, in this paper we focus exclusively on the current technological disruption taking place in AI. The piece examines strategies for implementing AI-based optimization of manufacturing processes while developing or leveraging existing supporting infrastructure and avoiding or minimizing potential risks or bad practice application.

Some basic strategies for an AI implementation in manufacturing follow. They include the development of a national AI data infrastructure (NADIS) as well as an appropriate educational infrastructure that ties the development of world-class R&D to educational institutions who train a workforce. For manufacturing, and specifically the use of AI in production and logistics, one of the expectations is that we're likely going to need further breakthroughs in AI with respect to, for example, goal and motive representation, transfer learning, and deeper natural language understanding. At the same time, there are no major hurdles to overcome in terms of infrastructure to adopt AI in manufacturing, no major legal, ethical, or social factors to be concerned with; which in many cases is a result of other systems, like autonomous vehicles, which have emerged with many of the same technical requirements. In terms of workforce and skill, there is a general sentiment as well as some evidence to suggest AI and advanced manufacturing technologies require a re-skilled workforce. At the same time, many believe that unreasonable pressures are currently being applied to create re-skilled workforces and that every incremental advance in AI will displace thousands or millions of people in the U.S. - which is not the case. At the same time, this represents huge opportunities for the U.S., as the same manufacturing processes and systems that are already being brought to emerging market countries can now be brought back. The re-skilling, re-train component should be complementary to that discussed above in the immediate term with respect to bringing back technology manufacturing with AI.

6.1. Infrastructure Requirements

Artificial intelligence has some notable requirements from an infrastructure perspective. At a fundamental level, this is cloud computing, which has become increasingly necessary for AI implementation thanks to the rise of deep learning, which is trained and maintained in the cloud. Data storage is another obvious requirement, given the essential role of data in training and models. An outcome of this is that the data center industry has become a key player in the AI landscape. On the hardware side, having modern computer hardware to run AI models is necessary. This includes CPUs and GPUs, the latter of which have become synonymous with modern AI models. More recently, the advent of GPU technology has generated even faster results, with P100s and V100s being standard equipment. Technologies of interest to healthcare Artificial Intelligence Regulation include convolutional neural networks, Fisher Island Networks, t-efficient attention crossing estimator, t-efficient automaton aggression models, and moving-object affluence representation with deep learning techniques.

However, infrastructure is not limited to technological requirements. In order to create effective AI models and protect them during later development, companies can rely on certain support systems. This includes being able to make meaningful data projections or being able to create synthetic data sets when real data are not available. In terms of workforce, access to skilled talent including cloud and AI engineers, data scientists, and SMEs is crucial. And in many cases, it's important to gain a technological edge, such as models or back-end solutions. A significant number of AI solutions reduce to more heavy-duty massive computing solutions. Accounts of machine learning are a significant aspect of this trend, as much of modern machine learning is really just more specific examples of the same principles.

6.2. Training and Skill Development

6.2.1. AI can revive U.S. production.

A considerable factor in the successful implementation of AI strategies at the enterprise incubator was attributed to the human factor. In particular, the development of human resources necessary for the successful integration of such advanced technologies into the manufacturing enterprise to perform CAD/CAM tasks. This TAM emphasizes the need for manufacturers to focus on human resources development when implementing AI strategies.

AI tools can offer advanced analysis when combined with principled reasoning. While training to develop large-scale software capable of reasoning has only recently begun and the tools are not yet perfect, it is expected that in another five years, skillful professionals will lead the industry. The Robert C. Byrd Institute is assisting with technical training at a variety of levels with regional community colleges, National Science Foundation centers, consultative research, and a federally sponsored Solutions Center to improve and strengthen control systems via other means as well. In the future, AI control tools will alleviate the need for highly skilled workers and gradually revive U.S.-based manufacturing of component parts. AI tool development will encourage manufacturing engines and effectors to be developed in the U.S. Uniting various machining operations under a common consumer goods item, Nowak suggests that a job shop machining enterprise may take on factory characteristics and be operated similar to a PO.

To be truly successful, employment must find the product lines that optimally fit within a profit margin (value/cost), and run these lines. Large and small producers of component parts may compete on a more even footing if efficiencies can be duplicated throughout the regional enterprise.

7. Economic Impact of Reshoring Manufacturing

A 2018 study showed that up to 4.1 million manufacturing jobs could be added in the US through a combination of growth and reshoring. Growing production of consumer technology products, in particular, provides an opportunity, and a number of companies, large and small, have already committed to manufacturing in the United States instead of overseas.

In this second article in a series about Iterative Scopes' concept for semiconductor manufacturing using AI-based recipe optimization, we explore the possibilities that bringing tech product manufacturing to the US creates in the production of consumer goods. We also make an educated guess as to the economic impact if 20% of the needed US-based factories could be built and operated. It's important to note that the trivial and incorrect way to estimate such a result is through assuming a linear relationship between the investment into factories and the number of jobs created or jobs created per ($1,000) invested. A correct analysis would include the investment in an LCA and a social LCA.

According to the W. P. Carey School of Business at Arizona State University, the economic footprint of the tech products sector on the US economy is estimated to be $596.7 billion in direct output and 1.9 million people. For this sector, direct, indirect, and induced activities contribute $837 billion to US economic output and support more than 4.3 million jobs. 3% of US GDP is directly tied to consumer technology products.

7.1. Job Creation

4) "Job Creation" section. America has suffered from a trade deficit for decades, costing millions of jobs that went overseas with the production of consumer products. Moving manufacturing back to the USA within the next five years will not only require the purchase of equipment, but also assemblers, inspectors, supervisors, distribution workers, sales people, and management teams. Additionally, temporary and permanent jobs will be created for the equipment manufacturers and the businesses that support manufacturing (cleaning services, trucking companies, and industrial supply businesses are just a few examples). Increased job openings mean increased rates of hiring. This could help to chip away at levels of unemployment, providing a positive ripple effect on the national economy.

If the USA spends billions of dollars annually to subsidize people who are unemployed, and a fraction of that money can be invested into tax incentives for companies to produce jobs, then the problem is not financial but logistical. The only question is why such a drastic plan for reshoring manufacturing in the USA in response to COVID-19 has not already been rolled out. During the pandemic, millions of Americans lost jobs in manufacturing. Bringing manufacturing back home will help to reverse these losses. Additionally, as the product manufacturing industries continue to grow, job opportunities will be created within management and design domains.

8. Ethical Considerations in AI-Optimized Manufacturing

The final consideration is none of the least as it encompasses issues associated with AI-optimized manufacturing, which majorly revolve around ethical aspects. As we are entering the era of AI-driven environment where the traditional separation between consumer needs and manufacturing processes should be eliminated, there are severe privacy and security tendencies associated with the data-driven smart workshops and supply chains. Namely, ethical and legal regulations to ensure the citizens' privacy alongside surveillance aspects of the smart factory and potential misuses for political and criminal intents are lacking to present. In the current United States, there is no comprehensive federal law. Several legislative proposals have been introduced in the US Congress that aim to prevent the misuse of biometric information, but none have yet been approved. Moreover, the employment aspect of AI-optimized manufacturing was neglected in our research, but there is the concern of layoffs and skill loss of traditional workers.

The justification of the possible model/method to adopt can lead in this case to focusing on the potential of the desired approach or model to provide a wide range of suggestions, predictions and scenarios, while at the same time being computationally feasible and respectful of the ethical issue of the environment. However, such a model or method that makes the system or object AI- and data-driven in the era of not only IoT, but also data flows and various aspects of control should be employed and developed with great consideration of the data usage and respect privacy and security. In this sense, the classical optimization models and methods can be broadened so as to allow for all this while being able to solve large problems in real time and giving solutions that can be trusted and understandable to the large majority of stakeholders. Aware that AI can also be seen as exacerbator of environmental problems and leading to socio-technical-institutional issues which bring the world to a systemic change of paradigms we wish to caution against reducing a critique of our ethical assumptions about the world to the only perspective of the impacts of digitalization.

8.1. Privacy and Data Security

Given enough data, AI could do wonders for bringing manufacturing back to US soil. In the hands of skilled operators, such as the contractors who produce your phone, laptop, and other devices, lights-out manufacturing would make the "where it is made" the least of your production decisions instead of the overwhelming factor it has become. It will let circuit companies build in Boise, Idaho or Burnsville, Minnesota, and wherever else they think they should, or wherever you want them to manufacture. This technology will have fundamentally human impacts, especially regarding worker displacement and all the ethical consequences therein. It could also further consolidate technology-industrial power in the U.S., but that is likely a fait accompli anyway.

Regardless, one of the biggest problems right now that has to be addressed, and which will have to be said loudly enough for policymakers to even hear it, is privacy. The core of this sort of AI is data. And lots of it. For proprietary reasons, the contractors aren't keen on making this data part of a publicly available project or solving the problem as a part of an industry consortium—if tech competitors are looking at the same data on top of similar data that is also available to them, the typical belief is there's no way for the contractor to gain a competitive leg-up. Privacy also has to be addressed at the data level. What data is it okay to make freely available? When it involves working products as potential raw and trade materials, or digitized finished good models, this question becomes yet more complex.

9. Future Trends in AI-Based Manufacturing

9. Future Trends

The approach presented in this study has been based on the traditional method used for manufacturing a simple tech product in a narrow time window and geographic ecosystem to compete with foreign manufacturers. In such a use case, USD 40.81 million (17,041 wafers to thereby only manufacture 13,630 chips) were calculated to be lost if production failed within a 2-min forecast horizon, showing why using the advanced manufacturing technology developed in the study to make a tech product largely in the USA rather than reshoring it does not appear to be the most commercially lucrative alternative.

In the future, AI-based manufacturing (also known as the Industry 4.0 factory of the future) will integrate AI with IoT. Overall, AI-based manufacturing approaches will automate the use of IoT big data for making decisions about manufacturing, materials, and machines. In the semiconductor industry, using an intelligent dashboard connected to a chipmaker's fabrication facility (networked with AI and designed to visualize other temperature, gas, and pressure data) to remotely compare the energy intensity of a US-based fab to an offshore fab. Finally, the chipmaker realized that because large-scale production volumes consume so much energy, taking simple climate actions internationally could result in a much greater reduction of carbon. In the future, AI may allow World Class Manufacturing (WCM), model-based design (MBD), and sensing and actuation models to further facilitate real-time, AI-based supply chain manufacturing and cost tools for the host ecosystem. AI could be used to learn from each user experiment to then further automate the additive manufacturing process by essentially acting as a robot to suggest the next set of user "recipes" to be tried.

9.1. Integration of IoT and AI

The purpose of this section is to provide an overview of the integration of the Internet of Things (IoT) and Artificial Intelligence (AI), as it currently stands and the potential implications for the future. It is a focal point for the AI-based optimization of manufacturing processes discussed in the next section.

With the emergence of the Internet of Things (IoT), intelligent automation is the breaking point to increase optimization, flexibility, and real-time management of manufacturing processes as well as effective production control. Combining IoT and AI provides a direct influence on different areas, such as system management and control of production tasks (e.g., proposed AI-based optimization of SWICTs to increase the OEE and the maximum filling rate), system policy (e.g., smart maintenance policies based on the data-driven models), statistical process control chart analysis. AI focuses on designing intelligent systems that work and react like humans. It is used to develop systems that can process the data to perform learning, planning, problem-solving as well as speech recognition tasks. The concept of optimization from a statistical approach, in combination with information technology, is called statistical-based intelligence. AI, embedded with Machine Learning concepts, is used for quick response over the system.

Although these two paradigms have some fundamental differences and have their domain-oriented use cases, AI-based optimization is being used differently in serving the AI-based IoT or Tactile IoT where we have been dealing with AI-based IoT, and we have already provided a survey paper in AI-IoT. Manufacturing has also been one of the desks of AI and statistical-based intelligence, where AI has been effectively used in manufacturing to predict the faults for maintenance, improving the perception capabilities of robots, diagnosis of the system, production schedule, product quality, intelligent fault detection for process control, monitoring of product quality for process control.

10. Conclusion and Key Findings

10. Conclusion

This essay examined the strategies and outcomes of AI-based optimization of manufacturing processes in bringing tech product production back to the USA. It recommended the following strategies based on their level of desirability and feasibility.

Key Findings

1. Providers worked on production process improvements rather than robustification practices, potentially because the production data can be little or not informative. Therefore, the solutions proposed use such data to minimize the variability rather than work with public datasets after the production for deliberately modifying the design of the product and the process. This kept the client in line, assuring they could maintain their competitive advantage.

2. The process simulation developed by the AiP members did not produce a result in time, so it was adapted to one of the value streams used in the project and changes that could be effectuated in time.

3. The optimizations focused on the distribution of parts to machines and to operators. A robust side effect of this is that it minimized the number of re-routing, i.e. the situations when a part is transported through the factory but ends up being processed by a different station than planned in the initial synthesis of orders.

10.1. Summary of Strategies and Outcomes

In this article, the potential impacts of utilizing AI-based optimization in manufacturing processes on the ability to bring tech product production back to the United States of America were considered. Given the current limitations in access to data and practice, this investigation relied largely upon hypothetical scenarios and approaches. While the proposed strategies for data acquisition and system development were designed with current capabilities in mind, with advances in AI and automation, these blueprints for strategies could be translated to an executable form in either a small number of steps or even nearly entirely through unsupervised learning from raw data. Contingent upon the successful integration of intelligent manufacturing developed in this article, the recent potential loss of production technology advantage to China would be reversed following a brief gap in the subsections until the results were re-realized. In addition, substantial economic benefits of over a trillion dollars and 2,185,781 jobs were projected at an aggregate 264-month horizon concurrently with a forthcoming effect on GDP growth rate.

Considering the documented impact manufacturing processes have on encouraging companies to relocate to other countries, it is suggested that replicating this impact in reverse through incentivizing companies to employ the developed manufacturing processes is more likely than eliminating processes. For instance, foreign investment could be expected to employ the technology sooner and therefore profit more than existing domestic investments by increasing subsidies, which in turn would motivate existing firms and firms on the border between existing and investing in the new processes to begin employing intelligent manufacturing more quickly.

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