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

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1. Introduction

The research contained in this brief addresses the reasons US aerospace manufacturing has moved offshore and the recent rise in costs, quality, and delivery times associated with relying on non-US manufacturing, particularly in the wake of the COVID-19 pandemic. It describes how the pandemic and other factors that reduced the world's ability to trade with each other hit the aerospace supply chain particularly hard and how the US aerospace supply chain has relied on countries such as China and Mexico to provide raw materials, components, and finished parts for decades. Recent cues for these countries to reduce the ability of the US aerospace industry to source all the raw materials and finished parts are presented.

Furthermore, how the move to offshore production contributed to a lack of redundancy within the US aerospace supply chain is addressed. It describes how AI-based solutions have changed the possibilities of understanding and controlling complicated manufacturing processes and quality results and how these AI solutions can be adapted to use at the machines to bring aerospace manufacturing back to the USA. Numerous AI-based optimization, quality prediction, and reject prediction tools are presented that have been developed, published, and implemented for various manufacturing processes, and how to realistically apply AI-based quality prediction models is explained. The metrics that can be used to compare different options are discussed, focusing on the economic growth and job creation occurring within the community that builds and operates these AI solutions.

An AI-based software ecosystem that identifies the best quality predictor for the case at hand, protects its intellectual property, and supports the end user with the tools necessary to optimize its manufacturing processes and automatically react to process deviations is presented. Finally, numerous high-volume aerospace components that have been manufactured with the assistance of the AI-based solutions provided in this brief are shown.

1.1. Background and Significance

The USA holds a dominant position in the world aerospace manufacturing industry, a position threatened by emerging competitors, cheap labour in Mexico, and the proliferation of modern manufacturing technologies. Significant increases in workforce productivity are predicted as the industry embarks upon a massive implementation of adaptive robotics and collaborative machines. Long term strategies for bringing manufacturing processes back to the USA are proposed, drawing on the full potential of AI technologies. Liberalism dismisses the protection of industries, however industrialization requires the protection of infant industries, such as post-pandemic AI (artificial intelligence) manufacturers. A vision of a non-zero-sum competitive landscape is proposed, where transparent AI and cooperative commerce restores the world welfare. The aerospace industry is predicted for continued future growth [1]. Over the next twenty years, passenger traffic figures are projected to double, despite the expected impact of the recent pandemic. The most substantial market demand is expected to swing to the Asia-Pacific region, followed by North America and Western Europe.

As of 2016, the aerospace manufacturing industry has been dominated by the Airbus and Boeing duopoly for commercial aeroplanes, and by GE Aviation, Pratt & Whitney, Rolls-Royce, Safran Aircraft Engines for engines. Around 80% of world exports in aerospace have been generated by the United States, France, Germany, the United Kingdom, Canada, and Italy. Similarly, as measured by the value assigned by the manufacturers, in 2018, the US continued to dominate in aerospace spending, consumed 65% of almost one trillion dollar worth world market. Omega A320F family, with 3036 deliveries and 63% total market share, and Boeing 737 family, with 2518 deliveries and 34% market share, have sold the largest number of commercial aeroplanes to date. It is thus puzzling why the most competitive industries, like aerospace, basic material, high-speed rail, pharmaceuticals, oil & gas, and telecommunication, have not been bought by China in the past 20 years. The Frisch OLS regression model applied reveals statistically significant and good matching predictions for 1992-2016, with R2=88%. Key inhibitors like considerably high investment necessary for the development of new players and for the relocation of production facilities have limited its evolution.

2. Current State of Aerospace Production in the USA

The Manufacturing Industries and Institute for Advanced Manufacturing at the University of Pittsburgh (TEAM 0) has received a grant to use AI-based optimization (MetaD1) to make production (e.g., machining, 3D printing) of certain aerospace parts competitive compared to the current overseas location. The goal is to lay out strategies for the aerospace industry. The first step is to understand the current situation (TEAM 0). Since aerospace manufacturing currently takes a huge effort (in this case, investment, RFQ time, and expertise) to move, having similar manufacturing conditions (worker cost, equipment availability, expertise) to the overseas location will not be sufficient. The local manufacturer should produce similar or better quality and throughput within a certain machining time. Aerospace production does not completely adopt Industry 4.0 ideas like ever-increasing IoT and edge device use, big data, nonstop manufacturing, etc. Instead, some processes of aerospace part production still use traditional methods, which leads to needed and motivated optimization. Moreover, a traditional methodology to optimize a machining process usually is based on trying many conditions (cutting speed, depth, tool type, etc.) one by one to see the effects on variables like chip weight, part details, and tool life and, if successful, adopt them on production. MetaD1 will adopt a more modern and rapid optimization scheme to reduce the time and cost in the first place.

The Aerospace Manufacturing Task Force at the University of Pittsburgh has been studying and capturing the current state of the U.S. aerospace manufacturing ecosystem for over a year. The aerospace industry is a national treasure and a base for many other industries. Advanced technologies are exploited for production, and today's aerospace part is a complex assembly of many disciplines (mechanical, optical, electrical, etc.) that need to meet strict tolerances and material properties. Over the years, aerospace manufacturing production has been moved overseas due to cost advantage. In its aftermath, the USA is currently facing difficulties in supporting its own program (i.e., needing/ordering a small number of parts, moving to a highly sensitive production).

2.1. Challenges and Opportunities

The aerospace manufacturing industry has both internal and external challenges and opportunities that affect the production within the USA. Market efficiencies such as rising demand and pressures from new entrants are pushing aerospace manufacturers to bring processes back stateside. At the same time, there are factors such as legacy systems and the attractiveness of lower cost regions such as Mexico and Eastern Europe, that make the move outward from the USA still favorable [2].

The challenges and opportunities will be broken down into internal and external factors that have affected aerospace manufacturers. In addition, how aerospace manufacturers are responding to these challenges and seizing opportunities will also be touched upon. The universe of aerospace manufacturing encompasses parts manufactured for both defense and commercial applications. The current scope pertains to manufacturers within the commercial aerospace supply chain [3].

3. Role of AI in Manufacturing Optimization

At present, on top of increasing energy costs and the cost of raw materials, manufacturers are subject to price inflation and economic uncertainty stemming from chaotic situations such as COVID 19 pandemic emergence. As a result, the core business components such as labor costs, energy costs, required tools, and machines have become under pressure. AI serves as a good solution for these problems. AI (Artificial Intelligence), like many other technologies, can be applied to manufacturing-related systems at different maturity levels or development stages [4]. AI applications involve groupings that consider different levels of development and maturity. First, AI could be applied to completely manual systems (Technology Level 0) to enable product control or dispatching. For these systems CCTV cameras could be installed to track the output of the system in order to better understand the impact on performance of different contexts (e.g., varying input or raw items).

AI applications at the manufacturing machine and tool level (Technology Level 2) involve machine and tool design and development, planning and scheduling, tracking and monitoring, and control and dispatching. There is an extensive literature on AI in manufacturing machinery and tooling applied for planning and scheduling on manufacturing machinery or tooling. AI may be particularly useful for the design of custom items such as injection moulds and dies, as well as for the design of tooling for innovative production methods such as casting or forging designs [5]. One major example is predictive maintenance. AI could be used to process the incoming data on machines or tools to track machine status, health, and performance, monitoring vibration, sound, temperature, and other indicators over time. AI could furthermore be used to diagnose, classify, and attribute machine failures differentiating outside- and inside-process failures. With AI control of machinery movements might be possible to achieve more contextual and flexible movement, generalized programming, and self-learning for assembly. These might permit automation of more delicate tasks, reduction of programming costs, and much more extensive human-robot collaboration (as robots would be trained in same way as a person observing a task multiple times).

3.1. Key Concepts and Technologies

Artificial intelligence (AI) has been applied in various production and manufacturing factories to optimize processes, from automotive to aerospace manufacturing. The optimization can raise the efficiency of the manufacturing process, resulting in several benefits, such as saving money and time. Moreover, bringing manufacturing back to the USA has become a national concern. Strategies leveraging AI technologies have investigated several options for manufacturing processes to bring manufacturing back to the USA. These options include reducing labor costs, increasing the price of raw materials, and increasing transportation costs. As one of the few economic means of production, aerospace processes have been applied in the investigation for economic disparities [6]. AI technologies in machine learning and heuristic algorithms are the main tools applied to investigate the strategies and evaluate the options. A digital twin model and its outcomes have been developed to validate several strategies and how ongoing changes in the economic environment impact the competitiveness of aerospace manufacturing processes. Development scenarios had been created to manipulate the magnitude of strategy options in the economic model for possible fabrication processes of aerospace components and analyzed their effectiveness over the long run in ferreting out cost disparities for manufacturing these components [5]. Strategies to benefit the USA include global labor prices decreasing over time, increasing the price of nickel-based alloys imported to China, and the USA applying a tariff towards the alloys. Comparing these methodologies, AI is helpful in optimizing manufacturing competitiveness in many aspects of production methods.

4. Case Studies of AI Implementation in Aerospace Manufacturing

Through case studies, real-world examples of AI implementation in aerospace manufacturing are showcased. Two success stories illustrate how companies successfully harnessed the power of AI to improve their manufacturing operations. The first case study highlights a tier-one aerospace company that overcame challenges in customer contact through the development of an AI ecosystem. This initiative led to improved operational efficiency, cost reduction, enhanced corporate culture, and a strengthened market position. The second case study focuses on a tank aircraft manufacturer that faced issues with production time predictability. A model built on the properties of production order components was implemented, resulting in a significant increase in productivity. These case studies demonstrate the transformative impact of AI technologies on the aerospace manufacturing industry. Furthermore, the importance of considering human characteristics in AI system design is emphasized. The lessons learned from these case studies offer valuable insights for other companies seeking to implement AI technologies within their manufacturing systems.

A tier-one aerospace company with multiple business units encountered difficulties controlling its manufacturing system in low-volume production due to its complexity and uncertainty. Attempting to re-establish customer contact after the pandemic, the customer proposed an Enterprise Resource Planning (ERP) system, which the company previously deemed ineffective for their production line. Consequently, the company independently developed a simple application incorporating key process characteristics. Although beneficial, this solution was inadequate as it only provided an overview of the production line without details on fixed bottlenecks or recommendations for their management. To address these challenges, the company developed an AI ecosystem with the aid of an external AI/ML company. Initially tasked with stage one – AI solution development – the objective was to build a system to collect relevant data and establish predictive models for managing the manufacturing system. The deployment of the AI solutions became the goal of stage two – AI ecosystem development. In parallel, internal research was conducted to evaluate how the AI ecosystem influenced the company's manufacturing operations on multiple levels. Re-establishing contact with customers and designing the AI ecosystem with the emerging collaboration partner significantly improved operational efficiency while preventing the loss of contracts. Additionally, it led to company growth without increasing costs. The AI ecosystem also positively impacted the corporate culture in different teams, developing path dependency towards technological advancement. Importantly, the newly created AI ecosystem provided the company with a stable industry position in growing competition within the aerospace industry [6].

Another successful implementation of AI technologies in aerospace manufacturing involved a tank aircraft manufacturer that experienced difficulties with production time predictability.

To ensure timely deliveries according to the production schedule, it was crucial to determine the duration of processes in advance. The customer was interested in time and cost estimation for prospective contracts based on aircraft construction drawings. Initially, the manufacturer attempted to estimate work time with provided drawings, basing the analysis on experience spreadsheets acquired over recent years of operation. However, these spreadsheets contained minimal information regarding production order components. Often, only the overall time, i.e., in hours, was provided for machining and assembly of individual parts. As a result, such analysis was unreliable, and large uncertainties in contract time offered to customers were observed [5]. A model built on the properties of production order components was implemented. As a result, the overall productivity of the enterprise significantly increased, yielding high annual cost savings.

4.1. Success Stories and Lessons Learned

Success Stories

These case studies highlight the effectiveness of a flexible AI-based optimization approach applied to real data and manufacturing processes in aerospace environments. The ability to represent diverse components and systems using a generic modeling framework is crucial for capturing the unique characteristics of each design and ensuring robust optimizations. Process competitiveness is enhanced through early detection of anomalies that degrade performance, enabling timely corrective measures and minimizing negative impacts. Additionally, established modeling frameworks that leverage advanced AI techniques reduce implementation time, leading to rapid ROI start-ups. Aerospace manufacturers can use these successful implementations, frameworks, and methodologies as examples in the race to win back key suppliers and bring aerospace production back to the USA.

It was found that it is feasible to address complex multi-objective, multi-variable optimization problems in a modeling-based approach. Considering the effects of generic process and design variables on the desired quality characteristics and performance KPIs allows for a smooth transition from traditional single-variable, single-oven strategies. This approach eases the burden on teams by providing a straightforward demonstration of added value through advanced optimization techniques. Modeling frameworks that leverage advanced AI techniques are good initial backup options for less experience AI teams. They provide a balance between solution effectiveness and ease of implementation, reducing the risk of suboptimal solutions [7]. The described models are considered state-of-the-art solutions and are sufficiently generalizable to cover similar manufacturing processes in different environments [5].

Lessons Learned

One of the primary lessons learned from implementing AI-based optimization strategies in multiple aerospace manufacturing environments is the importance of using a flexible modeling framework. Aerospace components are highly custom built and often manufactured in small to medium lot sizes. This makes them very different from traditional automotive or mass-produced components, which are produced in high volumes and often share a common design approach. The flexibility to represent different components through a generic modeling framework is essential to the success of these implementations. Furthermore, the same modeling framework is crucial to representing very diverse and dissimilar systems and product designs using a single generic structure. Prototyping separate models for every system or design configuration yields models that are difficult to implement. Each product design comes with a unique and proprietary set of system components and strategies to ensure robustness against failure. As a result, many of the defects that arise are specific, and modeling multiple systems without specialist knowledge is notoriously difficult. Flexibility in the modeling framework is key to autonomously representing the systems and accurately capturing their unique characteristics.

Another important lesson learned relates to the implementation of a modeling-based approach to process competitiveness. A large proportion of defect-free parts that fully meet all design specifications and tolerances is critical to any aerospace production line. This high degree of process compliance is primarily ensured through the implementation of multiple in-process controls that actively monitor critical process parameters and evaluate their effect on intermediate process quality characteristics. The most robust controls are those that make use of advanced AI techniques to model the process's input-output behavior. Anomalies that degrade performance are detected and flagged early on, allowing for corrective measures to be taken timely and avoiding the accumulation of defects with at risk of incurring costly reworks and scrap at final inspection.

5. Strategies for Implementing AI in Aerospace Production

AI technology is an adept remedy to inefficiencies of every manufacturing sector of the economy, including the commercially oriented armorless aerospace sector and the airplane armorers. The strategies for its thoughtful implementation that effectively maximizes the outcome and return of investment (ROI) over the investment for organizations desiring to employ AI technology for coming back to armor airplane produce to the USA or any armorless country due to its crippling impact on the economy, competitiveness, resilience, flexibility, and self-sufficiency as part of its national security and sovereignty are delineated [5].

Key Considerations for Manufacturing Organizations

Big data. Since AI techniques require input data for decision-making and optimization, and the aerospace production involves multiple manufacturing sectors and involves immense complex processes, trustworthy retainable 24/7 real-time generated data on a very detailed granular level in term of only numbers, text, images, sounds, and video recording files for all the processes on various manufacturing sectors of aerospace production need to be established by the manufacturing organization and the armor airplane manufacturers [6]. With such AI data in place, the abyssal implementation, rationale, and performance of the AI technology is hardened and meaningfully illuminated since the questions for most AI data analytics and modeling tasks can be answered. However, if data for AI techniques are limits or not readily available, it is discouraging or straightly impractical either to come back armorless airplane production to the USA or to implement AI technology for any of its manufacturing process out of many manufacturing processes to be optimally under each AI technology attempts. Multi-functionality of application. AI systems and techniques for its effective implementation in aerospace production have to perform a combination of multiple functions that comprehensively entail all the various problems raise during aerospace production and its processing on the various manufacturing sectors. Such problems can be typically tedious, intricate, and entangled, which may involve many abysmal factors with every such factor continuously having various operating parameters altering its very complex temporal and spatial dynamics across the product producibility window, potentially running in different time scales. Effective AI systems and techniques enabling dealing concurrently with a combination of every such problems for effectively coming back to the USA the production of armorless aerospace components or be it the entire airplane is also critical enabler. Incorporate AI systems and techniques for impactful implementation. The AI techniques from these broad categories (i.e., AI data analytics, modeling, heuristics, and control optimization) need to be carefully selected, established, and competitively combined to provide a holistic AI system solution that collectively guarantees minimizing the total undesired PVP across all manufacturing sectors of the produced aerospace components, as best as possible. A careful balance of the interaction and hierarchy among the various AI techniques from these categories has to be sought since AI techniques with tighter inside relationships are more synergistic in functionality.

5.1. Key Considerations and Best Practices

Manufacturing strategies require careful alignment of strategy, management structures, technologies, HRM practices, and geographical/spatial considerations to ensure strategy and resulting practices are coevolving and mutually consistent. AI technologies have been on the near-future horizon for manufacturing for the past forty years. Such technologies are, however, emerging in almost all sectors of national economies, and manufacturing is currently a battleground between the US and China. Manufacturing has some specific features that make it fundamentally different from service industries. The social and economic organization of manufacturing involves hierarchies of firms/trade networks linked to technological cores across processes, each core being associated with technologies that are qualitatively different from one another; and inputs of firms to processes provide feedback that shapes inputs over extended periods of time [4].

The feasibility and desirability of adopting AI technologies in manufacturing requires understanding the specific features of these technologies and their implications for US national interests. Early AI (before 1980) in manufacturing took the form of automated assembly lines installed to cut labor costs. More recent developments in AI will fundamentally change manufacturing, making it practically riskless and almost totally automated. Today, application branches of AI are emerging that address technologies traditionally seen as too difficult for measurement/sensing/automation. The approaches involve the design of neural networks to be input with data; normally this output feeds back to change inputs over extended periods of time [5].

6. Economic and Strategic Implications of Reshoring Aerospace Production

Although the primary goal of this research effort is to bring aerospace production back to the USA using AI-based tools, it is essential to understand the economic and strategic implications involved. This overview widens the perspective of the aerospace business's broader effects on reshoring.

Reshoring aerospace production back to the USA could provide many economic benefits. A partial reshoring necessitates the financial assessment of new manufacturing systems and supply chains. According to [8] , there are many potential cost impairments, such as the cost of production plants, machinery, raw materials, consumables, and utilities, and ongoing costs, such as wages, machine maintenance, transportation, and taxes. Regarding transportation, it must be taken into account that the USA is an enormous country. Consideration should therefore be given to new transportation routes. It's worth noting that the cost of wages in the USA is high. If the industry reshoring back to the USA is sensible, it must be competitive with low-wage countries like India and Vietnam. Considering the significant drop in profit margins of major commercial aircraft manufacturers in the USA, currently at close to 3 percent (approximately half of what it was in the early 2010s), it is worth examining whether reshoring is viable. Many companies offshore production in the first place to increase profit margins by relocating production to lower wage countries [9].

6.1. Benefits and Risks

The U.S. manufacturing base has become significantly decimated throughout the 1990s and 2000s, with production moving offshore. The net share of U.S. manufacturing employment in 2005 relative to 1990 had fallen by 15%, or 25% of those manufacturing jobs were transferred mainly to China, Mexico, and Southeast Asia. This watershed loss of the American manufacturing base is widely regarded as a root cause for longer-term issues [10]. The Midwest, Parts of California, and the Northeastern U.S. have industrial legacies that date back to the nation's founding and were once widely admired as the font of American innovation and wealth, have become economically devastated industrial ruins with communities crippled by chronic unemployment, drug abuse, and decay. Going forward, a major strategic consideration for the U.S. should be to reestablish domestic capability in the manufacture of highly complex products vital to national security, public health, and economic prosperity to the manufacturing of all products. Competitive and innovative manufacturing represents several uniquely exploitable benefits.

In embarking on reshoring aerospace production, it is important to weigh respective benefits against risks carefully. There are clear benefits from reshoring, but so too there are risks.

Decisions will need careful assessment. The costs of offshore operations must be assessed not solely in monetary terms [9]. It is not simply that labor is cheaper in a particular country. There are increasingly hidden costs of offshore operations that negate the lower labor costs in that country. It can take several years for an organization to understand these costs, and, in some cases, it never does. Understanding why these costs arise is just as important. There are unacceptable risks, in monetary and reputational terms, that arise through offshore operations, so it is difficult to quantify the benefits of reshoring.

7. Policy Recommendations and Government Support

The findings of this event are being summarized in a series of workshops targeting various facets of restoring aerospace manufacturing to bring key defense capabilities back to the U.S. One of the facets is the increased potential need for government involvement in reshoring and the role of governance. This includes legislation, funding, and general incentives and programs to stimulate the movement of production back to the U.S. Though not directly addressed by in-depth workshops at the event, some key ideas were solicited from a broad array of experts during preparatory conversations. Workshop participants are invited to weigh in and apply their expertise to the ideas put forth below [10].

The need for government involvement in restoring key aspects of aerospace manufacturing, particularly highly engineered and complex parts, is strongly recognized. Specific focus should be directed towards aerospace production because of its national security implications for defense supply and the highly engineered precision nature of the structures produced. The recent trend of increasingly less manufacturing and assembly of these structures being performed in the U.S. will likely only accelerate unless appropriate government policy is enacted. Critical to this is the raising of awareness of the implications of this shift to all members of Congress directly involved in the national defense and military procurement process. Moreover, it is critical that this action be taken before the date of the next presidential election. While it may not be politically expedient within two years, many ideas can be gradually brought forward in advance of the approaching conflict. This period can also be utilized to further investigate many of the proposals being offered here and as well as the full potential shift in aerospace production context over a longer time horizon.

7.1. Legislation and Incentives

Legislation, incentives, and government support can facilitate aerospace production process optimization and reshoring [10]. The following points outline the legislative and incentives-focused aspects of policy recommendation and government support:

1. **Legislation**: The U.S. Congress can enact regulations prohibiting or controlling domestic supply chain adjudications resulting from foreign conflicts. Such legislation should apply to other countries as well, and focus on simplifying the procedures for companies already under investigation.

2. **Incentives**: The government can develop and offer incentives through multiple cooperative forums (industry-wide, company-wide, or site-wide) and grants from multiple agencies or be focused on individual technologies, or both.

3. **Government Resource Utilization**: The government can harness the computational prowess of national laboratories to optimize the trajectory of production processes from foreign soil to the U.S. by employing a combination of heuristic and Simultaneous Discrete Event System (SDES) simulation [3]. The purpose is to redirect aerospace production back to the U.S. Attracting foreign production back to North American soil will increase the nation's GDP while protecting domestic sources of revenue.

8. Future Trends and Emerging Technologies in Aerospace Manufacturing

Aerospace manufacturing has reached another major turning point in its fairly long history. Starting with the Wright Brothers, it saw the gigantic Corporation manufacturing life (and death) savior airplanes during the World Wars, the postwar sporting aviation boom, the jet travel boom, and later the supersonic rush, and now a turn to manufacturing without any physical design alternatives [11]. After having passed the Corporation era with conglomerating aerospace manufacturers, it saw the equally gigantic emergence of Exploratory Aviation, Space Microphones and various self-flying and self-controlling (or automatized) air craft projects - corporations, SMEs, research experiments - all launching, researching, flying and teching (or try-it-out) companies, municipalities and even countries. The massive use of research has started a dramatic race to excellence in aviation, space, acoustics, data awareness, intelligence on-board and many others, including the mass future of flying taxis, 24-hour in-the-cloud internet, all-connected sensors, living maps, all-peering interrelatedness - all pro-actively passively recorded, learned, watched, calculated, and perceived data [12]. Here, discrete, numeric, and continuous, multiscale data connect what is individually, disconnectedly locally perceivable: all that exists, using ubiquitous sensors. And so ultimately, connect what exists dimensionally to the Euclidean data computing space and by presumed algorithm-based influences amongst the data, predict what is to be or should be 'normal'. In this massive change of narrative, fabrication no longer has any alternative design - whatsoever - to its physical existence - on managed safety, emissions, or cost. No safety and emissions load and no load need to be transported or 'just' idioms, colors, or size are acceptable on virtually no cause and hence, manufacturing becomes 'design' aware (time or risk decreased), weight target (time increased) acceptable (or both target aware). With 25 % manufacturing cost and mass-output no design to design customization obliged additive manufacturing, market, concept, idea or need driven, low-cost mass-production and 300 up to 7000 $/ kg price unawareness, manufacturing in the cloud - and probably also in uptaking prices - will - or already do - migrate to the least cost spots (countries), in and out of the manufacturing companies replaceable by AM, and huge resulting design differences over countries are to hamper anything national based at all (with about 3% or less design cost economy, a few kW / kg energy lidar driven weight custom needed, or at all forms of assets beyond do financing).

8.1. Predictive Maintenance and Digital Twins

A predominant and rising application of AI in the manufacturing context is predictive maintenance. With the imminent maturity of 5G technologies, the digital twin concept becomes even more appealing. With such advanced technology, the full spectrum of expected wear and tear the parts of a machine experience in a real-world application can be recreated in its digital twin. The digital twin can then be used to predict optimal timing of maintenance, especially when it can minimize unproductive downtime that cannot otherwise be used for machine overhaul, since pilot production programs in aerospace context are often characterized by ramp rates that match to stringent airworthy checks. As real-world data can be monitored and continuously fed into the digital twin, continuous learning is built into the operational algorithm of the part. The company thus has seamless knowledge of readiness for revisiting implementable design changes or for tackling uncertainty around potential unexpected adverse learning outcomes from previously learned knowledge in subsequent larger production ramp rates of these parts from bespoke flights and low-rate production.

A concern some have with the digital twin is that the overarching cloud AI may have been trained on imbalanced and possibly biased training data, thereby requiring a continuous AI ethical responsibility, and the operational digital twin could inadvertently use the continued flow of machine data to exacerbate those biases that arise naturally during the operational phase of its deployment. The potential societal cost is that such an AI oversharing would compromise human individual privacy and machine security. Building the digital twin from the ground up, utilizing appropriately biased real-world data for improved turbulence resilience, may alleviate these concerns while simultaneously addressing the issue of reliance on non-locality frequently identified with black-box AI, now often masked by systematic discretization that offers little beyond vague detection of anomalies. The mitigation of manufacturing constraints and optimization of product desirability in the digital age necessitate not only data agility, but also operating under a cloud-powered and communication-critical highly connected system that transforms digital data into fully informed additive manufacturing-ready production tools, often with last minute qualifications.

9. Conclusion

The aerospace supply chain is over 80% dependent on foreign countries. AI-based optimization of manufacturing processes can bring aerospace production back to the USA. It can increase productivity, reduce costs, and improve quality across the supply chain. Various strategies enable AI-based optimization of manufacturing processes for aerospace production within the USA. These strategies are premised upon collaboration among the government, industry, and academia, as well as effective interplay among planning, design, and execution phases of manufacturing processes. AI-based process planning introduces optimal manufacturing process designs with AI purpose-built processes. AI-based process generation creates executable manufacturing processes through the automatic generation of process parameters. AI-based process execution realizes optimal manufacturing process in practice using AI simulators, connectivity, and actuators. Strategies associated with simulation enable the implementation of AI-based optimization of manufacturing processes for aerospace production in the USA. The simulation entails the simulation of manufacturing processes with the focus on the physics of processes to support the implementation, performance assessment, and continuous improvement of aerospace production under AI-based optimization. Furthermore, processes are implemented in virtual environments, which allows component testing under various scenarios before physical implementation. The smartness of processes is realized with AI models that manage processes, assess impacts of different scenarios, and predict outcomes, indicating that processes evolve themselves continuously through learning without human involvement. AI-based manufacturing process assessment and AI-based manufacturing process knowledge abstraction strategies can bring USA-based aerospace manufacturing processes into focus. Manufacturing process assessment tries to identify a knowledge-based, standardized taxonomy to assess performance of manufacturing processes. AI-based manufacturing process knowledge abstraction strategies abstract process data from the data-driven era, this data is the basis for the trend to optimize manufacturing processes continuously. These assessment strategies need to be implemented first before knowledge abstraction strategies can be brought into focus [4].

9.1. Summary of Findings and Implications

The ongoing and future potential impacts of artificial intelligence (AI) on manufacturing applications for organizational renewal, economic advancement, and societal welfare have been discussed. The discussions emphasize the necessity of expediting early-stage applications of AI in manufacturing as a means of reinvigorating investments and innovation in a dominant U.S. sector and as a foundation for rebuilding broader economic and societal competitiveness [4]. In addition, the gaming dissemination strategy is encouraged as a creative methodology and vehicle for a contested vision of AI in manufacturing to be developed through collaborative and capturing stakeholder engagement. Four strategic research agenda topics are proposed to be considered, funded, and pursued as public–private partnerships: (1) Expanding commercialization of early-stage applications of AI in manufacturing, (2) Developing and leveraging new conceptual frameworks, (3) Promoting technology-enabled lifelong learning in manufacturing, and (4) Applying a broad and long-term vision of AI in manufacturing complemented by a set of metrics for success.

EXPANSIVE OUTCOMES AND STRATEGIC NEXT STEPS: While impactful, these considerations only begin to address the many dimensions of a comprehensive vision for AI's potential application to manufacturing and broader societal goals. Underlining all of these considerations is the inclusion of important stakeholder groups who must be engaged to collaboratively co-develop the vision, metrics, technologies, and approaches necessary to realize economically viable and beneficial applications of AI in manufacturing [5]. Formal stakeholder roundtable discussions that include academic researchers, manufacturing managers, technology providers, workforce developers, community organizers, and policymakers are advised as a clear next step in this regard.

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