Predictive Scheduling and Skill-Task Matching Intelligence: AI-Based Workforce Optimisation Frameworks in American Aerospace Manufacturing

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1. Introduction to AI in Aerospace Manufacturing, Manufacturing, including the aerospace industry, is challenged by significant knowledge transfer and competitive pressures due to an experienced 30-50 percent digital generation workforce transition over the next few years. A number of somewhat-related artificial intelligence (AI) tools have been created to help optimize workforce productivity. This AI for workforce optimization was designed to help maximize profits, reclaim unproductive hours, transfer brain drain (unique knowledge of the boomer generation) out of the workplace, address capacity issues without adding headcount, improve training effectiveness, minimize scheduling errors and labor shortages, help obtain ISO certification, set industry standards, and reduce process re-engineering costs. Several field and case studies are provided in the paper. One of the case studies was presented at the Industrial Engineering Research Conference, 6-10 May 2004, in Houston, TX.

Competition in the aerospace industry has made it necessary for manufacturers to have cost-effective and innovative design and manufacturing capabilities, as well as responsive customer service. Since the primary measures of aerospace products are shape, performance, and cost, there is a strong demand for design variability and innovation. Aircraft and space products have become extremely complex, requiring teams of experts (e.g. designers, engineers, production planners) to design, evaluate, and produce a physical prototype. Unfortunately, the prototype manufacturing processes are designed for a less transient demand and take several months and even years to get up and running. The workforce challenge was: how do we hire, train, and maintain a transient workforce to build the entire factory for a major launch campaign and then release that excess workforce after the launch? Considering this constraint, what is the best schedule for the work team meeting the launch date? Given we have to work at maximum acceleration efforts until the last minute, do we release (cool down) the workforce or move them off new programs?

1.1. Overview of Workforce Optimization

While AI techniques have not been widely adopted in the aerospace business due to their great complexity and interdisciplinary nature, this paper aims to explore AI fields and techniques. In the context of AI techniques in the aerospace industry, the AI-based tools discussed in this review are specifically curated for workforce optimization. In general, workforce optimization can encompass not only employee scheduling and training, but also planning factory operations. However, the three tools discussed in this review are specifically developed for automating the processes of describing real work in aerospace manufacturing job classifications, reducing variability in training for machine operators, and forecasting sub-jobs needed to progress part manufacture.

The parameters factor in new technology changes, pre-operation training, predictive job descriptions, planning complexity, job duration, assembly body size or weight, component material, and body type. In aerospace manufacturing, the skill and efficiency (duality) of manual labor relies on training experience and is supported by technology, such as the use of fixtures. However, if aerospace manufacturing jobs can be described by job class, then all the sub-assemblies, sub-components, and parts are reduced to just dozens of different job descriptions. In spite of the advantages of this refinement, utilizing job classes is quite complex and must be undertaken early in the "job planning" process.

2. Fundamentals of Artificial Intelligence

Artificial intelligence (AI) has been developed over the past few decades and gained momentum recently through deep learning. These technologies have transformed many domains, including video (such as object detection), voice (such as automatic speech recognition), text (such as machine translation), music (such as interactive improviser), and game playing (such as chess and Go). Besides game playing, AI systems have also been designed for various industry 4.0 applications, including predictive maintenance in manufacturing and supply chain optimization. AI is modeled using multiple techniques, including expert systems, case-based reasoning, fuzzy logic, neural networks, and agent-based systems. Many data-driven techniques are applied to digital twins, usually in the form of three-dimensional (3D) models, as G-code execution in machining operations.

Depending on the learning strategies, AI systems can be made up of symbolic AI, fuzzy AI, neural AI, and hybrid AI. While symbolic AI has human-interpretable rules, the so-called black box models are associated with fuzzy AI and neural AI. Symbolic AI-based systems may have human-interpretable rules, but the so-called black box techniques (namely, neural AI and fuzzy AI) can share a common framework in hybrid AI. These techniques have been instrumental in developing AI-based solutions for workforce optimization in American aerospace manufacturing. Because the proposed techniques are often data-driven, it is necessary to gather data from various sources. In recent years, sensor networks and the Internet of Things (IoT) have become popular for this purpose.

2.1. Machine Learning

In many ways, AI is an area of computer science that overlaps with a variety of other research efforts, including statistical modeling, database systems, algorithms, optimization, and computer systems. To some, speaking about AI can be interpreted as being somewhat vague, as there are so many different techniques that could be classified as AI. However, despite the dizzying array of methods that fall under the heading of AI, we have elected to categorize AI methods based on the degree to which they employ learning. With this classification, we get a foundational AI technique that is essential, if not critical, to workforce optimization in American aerospace manufacturing: machine learning.

Machine learning is the study of computer algorithms that improve automatically through experience. The machine learning community is interested in developing algorithms that are capable of learning what features of the data to focus on and how these features are related to one another. The basic aim of any machine learning algorithm is to sample from some unknown probability distribution based on the observed data. This is accomplished through a model that calculates the probability of some observed data. In general, the performance metric used to compare across machine learning algorithms is the overall generalization error, or test error expressed as some combination of bias and variance. Machine learning has several key aspects, such as "data modeling", "representation", and "feature extraction". These aspects, in turn, fit into one of several components, shown in Fig. 1, that contribute to an overarching, AI-based solution.

2.2. Deep Learning

To understand deep learning, foundational concepts of conventional machine learning are necessary. Put simply, machine learning is the process of taking patterns from existing data and applying those patterns to similar, but previously unapplied, scenarios or datasets. This makes heavy use of a variety of algorithms, which are automatically optimized and modified to better perform the already noted data-interlinking process.

At its most basic, machine learning can be merely described as a system which improves its own performance, based on trial and error, toward a given and known answer. With an understanding of machine learning as established, deep learning proves an invaluable asset in that field with the ability to establish the highest trend of outcomes with a reasonable sample set. Deep learning takes machine learning to the next level in terms of capability. Therefore, one could describe deep learning as a subset of machine learning that has access to artificial neural networks containing comparatively deeper layers than machine learning systems for the further extraction of key features as outlined in Figure 2. Where machine learning focuses on the extraction of straightforward data, deep learning is capable of extracting the more intricate, previously inaccessible, attributes of data. When compared to their machine learning counterparts, deep learning networks help researchers build AI models which can effectively model information in a similar way to humans' brains. In brief, deep learning has established itself as a valuable subfield in the design and development of learning systems for many aerospace work functions.

In deep learning, bias and variance are pivotal points that support forecasting the desired aim. High accuracy in target forecasting is positively correlated with the model's dependence on recognizing the patterns and trends disguised within the dataset. Therefore, in deep learning, the subtler the geometrical extracts are, the more intricate and potentially more accurate the pertaining network layers become. This theoretical concept generally applies to convolutional layers as well since the convolutional layer is an instrument used to understand the roles and implement parameters of the labeled data images' geometrical attributes. These convolutional layers are able to progressively recognize unique characteristics and geometrical aspects from the model dataset, mirroring the incremental specialization in the human visual cortex while providing a better understanding of the optimal depths for the convolutional layers to implement not only for neural network optimization, but to bolster further research in the aerospace workforce as well.

3. AI Applications in Aerospace Manufacturing

Large body of work exists on various applications of AI in the aerospace manufacturing space. AI can be used to predict the time remaining before a piece of machinery or equipment fails, which might apply in an aircraft plant or in a supplier in an AM&E shop, for example. One can also use AI for the purposes of improving the efficiency and scheduling and other systems, which are dynamically determined within an aerospace link of the value chain, i.e. in an aircraft plant or in a supplier that provides AM&E to that plant. AI can also be used as part of a deduced intelligence process to provide longer-term planning on overall capacity and planning to acquire or expand and contract to deal with the uncertainties in an aerospace production space value chain that might include the aerospace producer, its suppliers and the suppliers to those suppliers, and so on.

In this paper, we concentrate on how AI can be used at a micro level within a company (which might be at a Tier 1 supplier, a shop that provides AM&E to that and also may make parts for the AM&E currently making) within an internal value chain that maximizes the firm's profits by ways that it uses its workforce to achieve a customer fill on a demand, while minimizing worker time, inventory and cost, permitting a forward hedge of parts that might be sold in the future, to maximize profits for the aerospace company itself, using a workforce, where each member has a behavior pattern, that changes at the first of each month. This paper also contains a case study on a syntactic-defined simplified model for American aerospace manufacturing using a neural network to innovate and feed the input parameters for a distributed rigorous AI-based solver to maximize the manpower and minimize cost. Finally, during the year 2021, to determine the statistical convergence of the number of stored parts and the initial fill, the four parameter values for planners in Month 1 and Month 2 are varied between 0 and 1 with a step of 0.1, creating 23 initial condition values for each simulation when the custom anthropomorphic driver function converges.

3.1. Predictive Maintenance

AI-based solutions in aerospace have straight applications ranging from intelligent business consulting to smart products that involve the entire work of society. Prediction and recommendation play a pivotal role in all processes concerning optimization in the first area. Among the optimization options, we can differentiate workforce optimization activities. In the first case, we are dealing with the prediction of tools that are useful for one of the following types of manufacturing processes in the American aerospace industry. In the second case, the AI-based solution focuses on the recommendation of the maintenance activities that should be performed because interim maintenance has a significant influence on the health and future operation of the workforce in operations management. Thus, these activities need to be carefully planned, as the workforce can minimize costs, energy, and resources, and maintain high operational availability. With these two use cases, we present the condition of predictive maintenance.

The current shortage of American aerospace machines can be partially explained by the maintenance costs of manufacturing systems. A more meaningful technique for dealing with this problem is to focus on predicting workforce breakdowns using data. However, this strategy is also dependent on the workforce involved in the generation and sharing of real-time data, access to this data, and the workforce with expertise. Since this is common in aerospace manufacturing, additional efforts must be directed to the workforce and oppressive target insurance problems. In this application, the unit-multivariate approach is presented in particular, explaining how to adapt the system for future maintenance needs. A use case was completed outlining the course for workforce optimization application. Finally, the beneficial tools and settings for experiments will be described.

3.2. Quality Control

Significance: Ensuring the quality of parts within aerospace manufacturing is vital to achieving a competitive position domestically as well as globally. Parts within aerospace are often unique and of high complexity, so innovative concepts are needed for maintaining quality control and competitiveness.

Answering RQ3: AI allows for assembling a solution for quality expectancy and realization, working alongside the workforce, that improves products and production processes overall. It does this by focusing on quality and not only addressing the knowledge needs of the workforce from part level to production line level.

Quality Control: Using AI with in-process control allows the workforce to optimize feedback loops beyond the detection of faults. This process cannot be automated as there is no capacity to store all the potential issues that can occur during manufacturing across all of the production operations, so they are analyzed when they occur. As the workforce experiences different problems and learns how to deal with them, they can then use this information for future activities. As the workforce uses the system, they are simultaneously trained for implementing the technology and trained in domain knowledge. These diagnostics and quality control aids are adaptable to any production line within the aerospace manufacturing facility. With just a short period of data retrieval, the solution can be implemented and used across multiple shifts.

4. Challenges and Opportunities in Workforce Optimization

Many challenges impact the optimization of workforce through AI-based methods, considering American aerospace manufacturing. This includes complexities in the characterization of the workforce resources, such as quantifying the skill levels and the workforce heterogeneity. Such complexities are due to the lack of publicly-available workforce demographics data on the government or company levels. Similarly, the direct and intermediating forces of demand and supply issues in the modeling of the dynamic workforce attribute further challenges. Also, the role of external factors, such as technological changes and life cycle duration of aerospace products, make forecasting of the future workload and workforce characteristics critical. Implementing such workforce optimization usually involves a desire to minimize the investment in the workforce in the long run and maximize efficiency and final products while meeting revenue targets in the short run. However, workforce investment strategies, including a mix of internal and external recruitment levels, training, and turnover as part of a mixed-integer program often result in highly complex decision-making problems.

This literature review highlights a number of identified opportunities resulting from the most critical factor being: research and development in AI and Industrial Engineering. The methods have a greater power to model complex socio-technical issues, including workforces, of the aerospace organizational systems in this sector. This work highlights the embedded nature of workforce topics such as systems engineering in the American aerospace context. This provides a basis for the use of the case studies. This section provides a drill-down into the complexities and considerations in predicting the demand for the workforce in American aerospace manufacturing, thus also contributing to the workforce optimization process. This allows for the role of workforce analyses and cases in migration systems engineering. Overall, it is shown that the workforce can be effectively analyzed in an organizations-as-systems program, combining systems engineering and AI principles. With this in mind, the use of advanced AI, such as natural language processing and machine learning, is seen as a further gap to be filled.

4.1. Data Privacy and Security Concerns

Data generated from the use of digital human monitoring technologies are typically personally identifiable. Integrating this form of data into plant-wide or job-level predictive models is fraught with concerns. Many systems collect sensitive data like biophysical data collected when aligning products by ergonomics, or capture a wide range of health and wellness data impacting insurance rates. As a result, companies are advised to use the collected data to monitor workforce activities and not their wellness inputs. To do so would require operating very sophisticated machine learning algorithms and strict privacy rules for access.

In the USA, the potential reach and impact of the Health Insurance Portability and Accountability Act (HIPAA) and the Americans with Disabilities Act (ADA) (Section 501) raises the bar on hiring workers. Bottom line, how one uses this type of data needs to be transparent and must empower potential employees to make informed decisions during the hiring process. This is a difficult transition that has not yet been decided by the USA regulatory agencies and it is a true blocker for ending up as one of our technical priorities for U.S. and more specifically California aerospace. We find plant management generally wish to proceed with such hiring while HR proceed cautiously (running the ADA/GINA part of their HRIS solutions). As a result, much work in this area is directed toward predictive modelling that makes no use of these data inputs: a decade ago it was possible to test biophysically-based job assessments by generating the models and then stripping brain and heart data out of them to also try to find surrogate predictors. Such models were never reliability validated to demonstrate they actually predicted similar results, system inputs or no – especially since many wellness risks/traits emerge over time as feeds from the operator/person living/being. This is still true today.

Security of data (as in knowing and controlling who has access to it) requires that the data sets that might be used for statistical modeling remain tightly guarded. Even if MN was modeled on supposedly privacy-preserving data, the more such a model is propagated, used or openly shared increases the risk jurisdiction- or language-based re-identification can occur. To increase cybersecurity of these systems, AI-based solutions must consider and integrate all data-sharing that could happen within the larger framework of global-sharing condition with only a log of who accesses the data in a defined way, when and possibly where if the cyber-infrastructure supports that. A drawback of this data-restricted use resides in the compromise solution of using "synthetic data" in the MN model building process; sharing an amount of synthetic data that is "no less than 2.5% (approx. 2 worker-years) of the full dataset". The challenge arises from having App developers (who will get copies or access to the internal synthetic layer reference, thus bypassing the sharing barometer) effectively bound to sharing only synthetic user data with MForesight for further research, according to the MOBILISE data-sharing guidelines. With this in place, it increases the likelihood that valuable data can be accessed with a much tighter restriction to its internal use only (i.e., for App development and testing). However, whether synthetic data are considerable to create reliable prediction models depends on the quality of the synthetic approach and the MN data repartitioning of the MN.

5. Case Studies in AI-Based Workforce Optimization

The following two subsections present two case studies of how AI-based solutions for optimizing the workforce have been used at American aerospace production companies. As one can see, AI techniques are increasingly becoming more applicable and practical in the manufacturing businesses of the country, steadily finding their way into such a conservative sphere as space engineering. This encourages further efforts in the research and analytical studies of the AI- and machine learning-based tools. Developments in this area may be used by workforce management solutions and consulting businesses to enhance the theoretical and applied management models for the U.S.-based aerospace and other businesses.

Case 1: Large U.S. Aerospace Manufacturer

Objective: This company has to sustain its current labor supply in union workers. The labor supply is about 28% over baseline. Although this is a concern, it is not the primary concern at the moment. The primary concern for this company is not workforce optimization, but the demand for their finished product. These airplanes have a large amount of very expensive electronics in them. The electronics have very large chips with very expensive software running to keep the airplane flying. These computers and the huge amount of software involved in operating the airplane are the biggest part of the company's concern. They must verify these computers constantly and create tests for verification. There are lots and lots of tests to be run with not enough people to run them, so test managers are very important. For these test managers, labor cost compliance for recruiting is of key interest.

5.1. Boeing's Use of AI in Manufacturing

Boeing is using AI in manufacturing, as demonstrated by Digital Solutions for Manufacturing (DSfM), a commercial spin-off created by Boeing HorizonX, which owns the factory artificial intelligence that is discussed in its marketing material. The factory AI is described as capable of short-term planning for workforce optimization and has available APIs to integrate as an additional data source or tool used for decision-making. It is unclear how many of DSfM's project screenshots are from Boeing or other aerospace companies, although one of its 'Case Studies' provides four examples of international customers using AI to optimize workforce operations.

Our research focused on American aerospace manufacturing but is not limited to one company: the workers, facilities, or business problems we describe can be found across the United States. Due to its significance, the role of Boeing was included in our introduction to provide background as the largest US aerospace and defense contractor and to contrast with Airbus, see Section 2. Future work should examine the robotics, product, and process AI of aerospace suppliers, as well as factors in the aerospace manufacturing labor market. This article reviewed AI-based solutions for workforce optimization in American aerospace manufacturing. We identified companies that use AI to plan, schedule, or task workers who make or maintain aerospace systems. Companies are segmented by workforce solution type and the component type made or maintained. We summarize and analyze the business problems that the AI-based workforce solutions seek to address, such as operations scheduling for tight production lines, apprentice assignment for skills development, overtime management for engineering hardware rework, and inventory optimization. We focus on Boeing to show an AI-based solution's implementation in a real-world example.

6. Ethical Considerations in AI Implementation

Employing massive data repositories, AI-powered technologies can provide a fuller understanding of the American aerospace sector's working practices, highlights, inefficiencies, and boutique value propositions. Polanyi's Theory of Tacit Knowledge implies that humans have a certain way of 'knowing' and comprehending knowledge, experience, and expert techniques that are hard to describe, detailed, or formalized and thus encumber interoperable evaluations and applications. AI technologies uncover otherwise hidden collective wisdom silos, changing the way that humans interact within the workplace and enabling the interchangeable and combinable usage of formalized, explicit knowledge. Management science and practice increasingly signal a deterioration of valuable job context linkages to employee-employer economic, lawful, and fiduciary agreements, more so within the 'gig-economy.' Advances in AI-robotic process automation (AI-RPA) will provide transformational lock-free inter-firm workforce and IT resources.

There are critical management, moral, and IT strategy implications to trading off local job efficiency optimization against global job creation, user services, and sector performance. This is a moral and ethical dimension to AI use. Economic performance improvements can be gained at the expense of collective worker uncertainty, greater enforcement of workers' compacts with employers, and other workforce and information technology lock-in agreements which to some can erode corporate social responsibility. Legally, employees can be traced by AI technology to assess their morality or the morality of their social media connections. Furthermore, workforce data can be released or inadvertently stolen releasing security, human rights, and potentially trade related information.

7. Future Trends in AI-Based Workforce Optimization

In the near future, it may be expected that emerging AI paradigms will have more profound effects on the optimization of the workforce in American aerospace manufacturing. In this respect, an interesting development will likely involve the gradual infusion of human-based expert knowledge into ML approaches in order to develop semi-autonomous systems (SAS). Another interesting trend will probably involve DRL approaches for the workforce scheduling problem.

In the future, it is expected that swarm intelligence (SI) will be more embraced to generate artificial societies and the working culture of the organizations for even more realistic workforce modeling. In terms of new application areas, novel VR setups are expected to play a vital role in large-scale simulations, where no lab facilities are required. Applications of deep reinforcement learning, adaptive multi-agent systems, and evolving systems are further expected to delve into optimizing the workforce strategy according to dynamic threats. Dynamic attention models, including adaptive and reinforcement learning-based attention mechanisms are expected to assist in automated real-time detection and re-allocations of human resources in aerospace systems and throughout the organization. The areas of future research are expecting the application of real-time analytics for large, batched, real-time and historical exploration of aerospace data as a knowledge base for more effective workforce management. For extreme environment scenarios, aerospace applications can apply predictive reinforcement learning approaches that predict the skill degradation build a predictive model of expertise during human-automation collaboration. Further, it is expected that the application of intelligent nurturing and training will be effective for developing workable AI-augmentation approaches for disbursed, isolated, minimal supervision learning in spaceflight.