Adaptive Labour Allocation and Productivity Modelling: AI-Based Workforce Optimisation Strategies in American Manufacturing Operations

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1. Introduction to Workforce Optimization in American Manufacturing, Manufacturing is an important sector for the American economy and gross domestics income. According to the 2020 American Community Survey conducted by the US Census Bureau, the American hiring employment and wage in the manufacturing sector are 12,234,123 employees and 119,491,920,000 dollars, respectively [1]. However, there are challenges in American manufacturing, such as COVID-19 pandemic, labor shortage, aging workforce, and energy price hikes. The above challenges make the difficult but important need for American manufacturers to be smarter, more productive, and employee-centered.

Workforce optimization is one solution to the above challenge. On one side, workforce optimization can be viewed as the outcomes, initiatives, strategies, policy, actions, either collectively or in parts, aimed at improving the overall or specific efficiency of the workforce in the company. On the other side, workforce optimization also refers to technologies, techniques, methods, mechanism, either collectively or in parts, that make optimization possible or implementable, including AI-based solutions. That is, AI-based solutions can be treated as a subclass of technologies for workforce optimization [2]. Workforce optimization includes three major aspects, including decision-making strategies, operational workflow, and productivity improvement.

2. The Role of AI in Workforce Optimization

The American manufacturing sector is facing a critical war for talent. Predictions estimate that the United States will be short 2.1M skilled workers by 2030, equating to a $1 trillion loss in revenue. With labor costs accounting for 60% of all manufacturing costs, manufacturers are focused on exploring new initiatives to optimize their workforce utilization. Organizations that reimagine, rethink, and redesign how they execute their most vital tasks will emerge from the war for talent. Artificial intelligence

(AI)-based solutions are one such transformative initiative that can dynamically engage with technology and people within the organization, enabling the organization to be asset-light, capital-efficient, quality-focused, responsive to customer needs, and integrated with business partners [3]. In other words, AI solutions are disruptive technologies that boost operational excellence to permit growth and profitability sustainably.

AI transformation has rich possibilities, including takeover, automation, outsourcing, augmentation, redesign, and growth. The most prominent among these is AI augmentation, the synergy between AI algorithms, digital technologies, and people and organizations. It implies a delicate balance between blending, initiating, orchestrating, or autonomously operating business processes by AI and humans. In the US manufacturing sector, AI augmentation enables AI-based operational excellence solutions. These solutions embrace AI technologies and applications for smart manufacturing and workforce optimization [4]. Smart manufacturing refers to an integrated system of digital technologies, data analytics, and intelligent software applications, enabling seamless flow and access to information across the manufacturing ecosystem (customers, suppliers, regulators, etc.). Such manufacturing environments access and share vast, diverse, and complex datasets, requiring algorithms and technologies to discover knowledge from data.

3. Key Challenges in Workforce Optimization in American Manufacturing

High-volume production environments like manufacturing plants depend on flexible and dependable workforce allocation to meet variations in demand. However, due to ever-changing customer demand affected by competition from low-wage countries and variations in customer sensitivity to prices, new manufacturing systems, practices, and strategies are required to optimize workforce allocation [5]. Real-time workforce allocation optimization problems are NP-hard and focusing on manual decision-making and finite choices creates inefficiencies, wastage, and economic loss. A new class of Artificial Intelligence-based solutions, developed to aid and/or replace manual decision making for workforce allocation optimization, attempts to address some of these issues by exploiting Artificial Intelligence techniques. These techniques can be integrated within existing manufacturing systems with few modifications and can choose from a much larger set of choices compared to manual decision making, ensuring better allocations. Implementations in American case-study manufacturing plants from the discrete part industry, working at high volume, low product variety, and low mix-it-up scenario, demonstrate the effectiveness of the proposed solutions' feasibility, chosen solution modifications, and achieved results [1]. Addressing the problems of Human Resource Planning (HRP) and Dynamic Worker Assignment (DWA) for process cells populated with robotic machines and manual workers, four Artificial Intelligence-based approaches leveraging a real-time database monitoring machining, stock handling, and allocating machines and workers—the job shift database—produced high-quality choices. An Artificial Intelligence-based HRP solution was ranked as the recommended solution, producing a feasible and high-quality choice and filtering out bad choices generated by the other solutions.

4. Techniques and Methods for AI-Based Workforce Optimization

The US manufacturing industry has faced significant challenges in recent years, including worker shortages due to the COVID-19 pandemic, an aging workforce, and the Great Resignation. Additionally, manufacturing has been largely offshored to low-cost regions, and COVID-19 has increased pressures due to disrupted supply chains and shortage. The current demand for qualified labor exceeds the manufacturing industry's available workforce, requiring innovative approaches to workforce optimization to maintain resilience, productivity, and visibility. AI-based solutions for workforce optimization are emerging within manufacturing, enhancing productivity, including recruitment and staffing, training and skill augmentation, shift planning and workforce assignment, and employee performance analysis and retention prediction. These are important upfront processes in the workforce management chain [1].

Manufacturers leverage AI for industrial process defect detection using sensors and video data, demand forecasting, semiconductor chip design, industrial visual inspection, product price prediction from technical sales systems, and customer requirements prediction using IoT data. These solutions serve as control towers, providing 100% visibility of production operations and process variations with complete resilience, thereby reducing manufacturing costs and increasing competitive advantages. Additionally, AI-based video analytics is used to monitor human-robot interactions and detect motions contrary to safety operation requirements, preventing accidents. Such AI-based solutions are developed by technology start-ups as SaaS models in partnership with Strategy Consultancies and Industrial Equipment Vendors [6].

5. 1.1 Data Collection and Preprocessing Techniques

This section presents the techniques and processes of data collection and preprocessing employed in the development of AI approaches for workforce optimization. Data collection and preprocessing are essential for the successful application of AI technologies, as they are crucial for the development of AI case studies and involve the techniques and procedures of data collection and preprocessing tailored to workforce optimization related to American manufacturing.

Strategies for the comprehensive collection of necessary data (including employee performance metrics, training and upskilling resources, employee profiles, daily business operations, and sector characteristics) from different sources (such as employees, management, training and upskilling programs, human resources, databases, ERP systems, and recruitment agencies) are introduced. These strategies include providing survey forms to employees and management regarding tasks, responsibilities, preferences, and skills; developing applications for task assignment and training that automatically logs task assignment and completion while collecting employee performance metrics; conducting interviews with management about sectors and strategic decisions; and gathering company data with a focus on health indicators [7]. Second, data preprocessing techniques that prepare the collected data for use by AI approaches (including outlier removal, granularity adjustment/aggregation, normalization, transformation, enhancing performance predictability, and bias checks) are detailed. The comprehensive presentation of techniques used to collect and preprocess data specifically related to workforce optimization showcases a key aspect of the scientific contributions achieved throughout this research.

6. 1.2 Machine Learning Algorithms for Workforce Optimization

Machine learning algorithms constitute an essential part of AI-based solutions created to tackle the problem of workforce optimization. A desired initial workforce assignment is iteratively altered by a set of defined techniques, with a goal to improve productivity quantified by an objective function. Thereby the objective function considers the personal scores of individual employees with respect to particular workstations, their total travel times, and total times away from the workstations. In conformity with [8] , a workforce can be optimally assigned to workstations through employment of the following machine learning algorithms: Case-Based Reasoning, Backpropagation Neural Network, Random Forest, Multi-Layer Perceptron, Shannon Neural Network, and Support Vector Machine.

A station allocation score represents a number of points related to a particular employee and a particular workstation calculable based on several characteristics of work performance. Case-Based Reasoning employs a set of previously stored station allocation decisions with respect to particular operators not included here as prior knowledge and a model is created. Backpropagation Neural Network learns the artificial neural network mapping function between input and output. Random Forest constructs a multitude of decision trees and assigns a value based on a majority of classes assigned to each tree. Within the Multi-Layer Perceptron a neural network constitutes three layers: input, hidden, and output layer enabling a wave form of information disturbance through individual neurons. Shannon Neural Network consists of two distinctive learning phases. Probabilistic neurons in the same structure as in the Multi-Layer Network comprise the output model. A Support Vector Machine algorithm aims to construct a hyperplane separating existing patterns establishing a decision surface within an n-dimensional space.

7. 1.3 Natural Language Processing for Text-Based Data Analysis

The workforce is a critical resource for manufacturing, and problems occur, for example, when employees disregard safety regulations or when people become fatigued and make mistakes. Textual data are also collected in the form of video images showing employees limitlessly. Text Mining extracts valuable information and patterns from text. In workforce-related incident description data by using text mining techniques, such as Natural Language Processing and Visual Mining that show the results from both aspects [9]. Knowledge of how rules are broken and how to approach an employee in a critical situation is derived from this analysis.

Text Mining is a process of analyzing text-based information seeking new and previously unknown information [10]. In general, the text mining process focuses on data pre-processing and text analysis. Data pre-processing includes, for example, text cleansing, text segmentation, and stop word removal. Text analysis identifies key concepts and relationships of the text and clusters and classifies documents. This approach has been used, for example, to analyze incident description data and detect topics that the description data cover. A topic model is built based on hidden patterns in the data.

8. 1.4 Computer Vision Applications in Workforce Monitoring

Particular attention has been paid to exploring computer vision applications in the domain of workforce monitoring from the perspective of the American manufacturing sector. Since the emergence and widespread adoption of Industry 4.0, workforce monitoring and supervision has become one of the key challenges. The existing computer vision-based techniques have been analyzed and reviewed, so that possible solutions can be proposed to reduce the cost of human monitoring and even satisfy the demand for high precision monitoring. Some typical applications using various computer vision technologies to enhance workforce monitoring in the manufacturing sector, including routine behavior monitoring, safety inspection, and productivity detection, are presented. In addition, the future trend of using computer vision in workforce monitoring has also been discussed [2].

Routine behaviors such as drinking water, stretching, chatting, playing with mobile phones, and even sleeping are non-working activities that may occur during work hours. In these situations, the productivity of the weekly and daily outputs will drastically decline. Besides this, in line balance assembly production, the work time specification is strictly defined in seconds, during which the operator's attention should focus fully on the current assembly task. Any distraction will inevitably lead to a heavy loss of production efficiency and abnormal operation. In this case, examining whether a worker is working is more important than identifying the exact workers. To reduce the cost of surveillance compared with hiring more security personnel by the supervisor, videos from the surveillance cameras can be utilized for the automation of routine behavior detection. This type of application is normally implemented in two steps [11]. First, the person of interest in the video frames is extracted with a person detection algorithm, and then, the action is analyzed based on the original RGB images or the pose information on the extracted regions.

9. 1.5 Integration of AI with IoT for Real-Time Monitoring

As the development of AI technology continues, more solutions are available to improve workforce accuracy, throughput, and efficiency. For instance, random adjustments of manufacturing workers may lead to performance inconsistencies. For workplace assembly tasks, inadequate education or lack of knowledge regarding the procedures may result in increased worker errors, inefficiencies, and production delays. Nevertheless, existing monitoring systems fail to develop intelligent solutions that automate performance assessment and real-time suggestions for worker monitoring [2]. The integration of AI with the Internet of Things (IoT) enables IoT devices to use existing AI technologies for real-time analysis of incoming data. For workplace development, IoT devices such as cameras and sensor-equipped wearable devices can use integral AI techniques to detect workers' motions in real-time and extract useful features for activity analysis. Overall, it is visible that the demand for solutions upon the integration of AI and IoT is huge.

The ability to implement real-time monitoring systems in a flexible manufacturing environment may significantly boost productivity and efficiency. Workers can follow suggestions from systems to fix their performance errors, maintain steady performance, and receive training to enhance the corresponding skills. In a large-scale environment with hundreds or thousands of workers, a real-time activity monitoring system is useful for fixing workers' behaviors in time. The first system uses a single RGB camera to detect tasks conducted by workers. A CNN framework is employed to identify workers' activity classes, including picking, welding, machine loading, etc. Then, a 3D action approach is implemented using a skeleton-based posture extraction technique to locate performance errors. Such a system can be installed in the workspace above windows or ceilings and thus does not interfere with workers' activities. In the second system, a head-mounted camera collects the viewpoint of workers to detect their task execution. CNNs are also incorporated into a deep architecture involving a multi-stream approach. Workers' head motions and RGB images are fused to achieve real-time activity analysis. Overall, the techniques are able to conduct workplace monitoring in a flexible environment without setting constraints or specific devices to workers.

10. 1.6 Predictive Analytics for Demand Forecasting

Demand forecasting plays a significant role in predicting future demand patterns, thereby aiding workforce optimization challenges. Various predictive analytics techniques ranging from statistical (e.g., ARIMA, exponential smoothing) to machine learning techniques (e.g., linear regression, decision trees, neural networks) have been explored in the literature. Statistical techniques are widely used due to their simplicity and interpretability [12]. In contrast, machine learning techniques can capture complex nonlinear patterns in the data. Typically, historical workforce data is made available to learning-based prediction models in which the relationship between historical demand and independent variables is identified and used for prediction. Moreover, demand projection can enhance workload management in the workplace [13] and aid broader job reallocations within organizations to reduce overall dissatisfaction levels. Although numerous techniques have been proposed, no commonly adopted demand prediction technique exists in the literature.

11. 1.7 Optimization Models for Resource Allocation

Optimum Resource Allocation Decision is another optimization model, often used in business processes. In this model, a business process is understood as a set of recurring activities conducted over time with the aim of achieving a particular organization goal. The activities can be categorized into types and are executed by heterogeneous resources such as human experts or machines. Therefore, the allocation of resources to the activities is crucial for business. One of the basic resource allocation goals is optimizing the work cost, which results from a combination of many costs comprising salaries of employed resources, infrastructure costs of machines and their maintenance, and fines for violations of service-level agreements (SLAs) that enforce deadlines in process. On the contrary, one model approaches the problem from its performance side in terms of timely results of the conducted activities [14]. Other presented goals are deviation from an ideal situation or combination of resource allocation goals. The allocation decisions, such as selection of a particular technology, resources, or their number, can be just one-time at the time of process modeling or can be adjusted during process execution in response to the environmental changes.

Most of the approaches make use of data concerning resources or business processes. The data can be either overt, then numerical parameters are generally available and can be manipulated within the models, or covert containing an infinitely complex environment of circumstances. Several solutions combine formulation of processes on Petri nets, which is a solid and formalized way to describe business processes, with simulation as a very flexible and intuitive method for observing behavior and performance of complex systems. They often focus on deterministic environments, where all variables are either clearly known or can be predicted, which simplifies providing simulation results as a response distribution [15]. On the contrary, in reality processes often take place in uncertain system conditions, where at least part of the parameters cannot be modeled or estimated accurately. The uncertainty may occur in both characteristics of activities and resources, e.g. times, priorities, or failures. Combining simulation with optimization methods is a growing area of research, which actively makes use of the capabilities of either approach. Most models involve merely human resources, while business processes can have different types of resources attached, then their current execution state does not depend on their current type.

12. 1.8 Simulation and Scenario Analysis in Workforce Planning

Simulation and scenario analysis are key components of AI-based workforce planning, enabling manufacturers to simulate various scenarios and evaluate their effects. Here, we discuss the implementation of these techniques and their capabilities to analyze different aspects of workforce planning, such as staffing levels, skill composition, shifts, and training policies. The development of these tools is supported through illustrative case studies using real data from American firms.

To address workforce planning challenges in manufacturing, AI-based optimization techniques using standard mixed-integer programming models are employed. These models formulate the workforce planning problem as a minimum-cost flow network [16]. Standard models actively used in practice are developed while addressing issues unique to American manufacturers. Additional advanced features are included in these models to consider the specific structuring of workforce planning methods. A comprehensive simulation framework using simulation-optimized numerical scenarios is also presented. Given the planning results, this simulation framework allows the estimation of hours worked, production output, workforce cost, and their distribution across labor categories and skills.

13. 1.9 Ethical Considerations in AI-Based Workforce Optimization

The discussion centers on the far-reaching ethical considerations that must be borne in mind to ensure that the AI is an accountable member of the workforce optimization process, commensurate with its importance and capabilities. At the deepest level, AI-driven optimization raises philosophical questions concerning machines' autonomy and decisions' agency and moral, legal, and economic responsibility. Paramount among them is the challenge of how to ensure that human workers are not displaced or reduced to a lower status relative to machines when machines become more capable than humans in the tasks upon which they have relied for their livelihoods [1]. This is a profound issue that goes beyond workforce optimization and is far from trivial. It invokes large questions about inequality, social discontent, mechanisms to ensure that the fruits of innovation are fairly and equitably distributed, and so forth. It is often remarked that the workforce optimization institute could be like protein folding and naïvely hope that things will happen to work out OK, but AI to medicine is far less metastable than AI to manufacturing. Many things could go wrong—there is a broad spectrum of undesirable agents and mechanisms for creating havoc.

There are challenges that come more closely under the optimization rubric. Even carefully supervised AI optimization could precipitate socially and economically undesirable states in situations where decision and design parameters are tightly coupled with the considerations driving the incentives for A4V [17]. In game-theoretic settings resulting from these tight couplings, the instantiation of agents can be anticipated to lead to ever-quickening tensions and richer behaviors, a common outcome of discrete but cheap negotiations. Stressors created by A4V can obviously worsen such situations, and the economic, social, and political consequences could be dire.

14. Case Studies in AI-Based Workforce Optimization

AI solutions for workforce optimization were implemented at various American manufacturing facilities, and their applications, methodologies, and outcomes are further explored in a series of case studies. Workforce planning (WFP) solutions were implemented to optimize overall operations. Each of the cases presents a unique scenario or set of workforce planning challenges specific to the organization. In these cases, an AI-based job assignment algorithm is used to match resources (workers) to various activities/jobs to optimize production targets under different specification constraints. In addition to resource/job pairing, the WFP solution incorporates a second AI-based algorithm that assists in the prediction of daily production targets based on historical data (e.g., hourly production rates). This intelligent target prediction further supports the optimal allocation of workers while also providing the client with the necessary insight to monitor and track overall daily production performance. Each case presents positive project outcomes, highlighting productivity increases, streamlined operations, and lowered workforce operational expenses [7].

The first case outlines how an AI-based WFP solution was implemented to improve production efficiency at an aerospace manufacturing facility specializing in the production of complex structural components assembled from multiple parts with unique surface treatments. Here, the WFP solution developed by the manufacturer was tailored specifically to target shop floor resources (workers and surface treatments) for job assignments while adhering to various resource constraints. The overall productivity across the machine shop was optimized, resulting in an overall production performance increase of 35%. Enhanced visibility of work schedules and streamlined operations was also achieved. The second case follows a similar WFP solution implementation at an automotive components manufacturer specializing in machining operations. Specific to this facility, the job assignment solutions across three machine types (multi-spindles, horizontal, and vertical machining centers) are analyzed and presented in detail, targeting an average performance increase of 20%. This was achieved with resource/job matching and daily production capacity insight for ongoing management. The third case outlines the implementation of an AI-based job assignment solution in a product assembly manufacturing facility specializing in home appliances assembly. Overall productivity across the entire assembly area was optimized, resulting in an increase in worker productivity by 15%.

15. 2.1 Case Study 1: Implementation of AI in a Large Manufacturing Plant

The first case study focuses on the implementation of AI technologies in a large manufacturing plant, highlighting the impact and transformation of the workforce through this digitalization process. The plant, located in the Midwest and operated by a Fortune 100 automotive company, employs nearly 3,000 personnel and consists of various operations such as stamping, welding, painting, and assembly. Historically, the production data was siloed, with several poorly integrated local control systems and batch data gathering for analysis and reporting. Although the workforce was considered highly skilled and capable of diagnosing and resolving a wide range of manufacturing issues effectively, the plant management wanted to enhance both the skill level and performance of the workforce, significantly reducing unplanned downtime and improving first-time quality. However, due to the more complex nature of the production systems and manufacturing processes over the decades, it became increasingly difficult for the relatively older workforce to maintain the same level of performance. To address these challenges, AI technologies were proposed to be deployed in a pilot program [7]. To facilitate this digitalization process, the manufacturing plant underwent a transformation of the existing IT infrastructure to enable the seamless sharing and flow of data between manufacturing execution systems, cloud platforms, and AI computation engines.

The second case study presents the implementation of AI technologies in a small manufacturer composed of 150+ personnel that learn to produce high-performance warheads for the defense industry. Before AI deployment, the mass production of extremely low-defect density products was considered unattainable due to limitations in the manufacturing processes, tools, and workforce. The production data mainly consisted of offline engineering, laboratory, and measurement data, and the workforce had little experience in data utilization for quality assurance. Safety performance was regarded as a higher priority than productivity, and the plant was suffering from poor on-time delivery and low production efficiency for years. To address these issues, opportunities for AI implementation to reshape the workforce and facilitate the leap of learning were sought. Before targeted digitization, the current data acquisition architecture was analyzed, considering the potential roadblocks inclusion of closed-loop data flow architecture [2].

16. 2.2 Case Study 2: AI-Driven Shift Scheduling and Task Assignment

This case study presents a manufacturing environment where shifts and tasks are assigned to production resources (machines) and workers. The company in question is an automotive supplier producing parts for the vehicle powertrains. Workers generally work in fixed shifts, and two scheduling problems are analyzed: performance and flexibility on shift assignment and task assignment. A mix of optimization and simulation is applied to find good solutions for both problems and analyze the obtained plans' performance.

The automotive supplier produces parts for the vehicle powertrains, such as camshafts and spindle shafts for crankshafts. Production is done on multi-stage machine lines: parts are manufactured in stages (machined operations) taking place on a sequence of machines connected by transfers. A subset of machines and workers is assigned to each production order, which brings a set of parts to produce and their due dates. Each worker is able to perform a specific set of tasks, and knowledge on how to operate machines on each task is necessary. Tasks involve transferring the parts from one machine to another or setting up the machine when changing the part type.

The study focuses on two shift scheduling problems. The first one considers planning shifts of production resources (machines and workers) aiming for performance. The second considers planning shifts on the same scene aiming for flexibility. The analyzed plans differ in how shifts are assigned to machines. Only a single shift type is assigned in the first problem, while in the second one machines have the possibility to change the allowed shift types for a given period. This way, machines with a lot of demand can be assigned to longer shifts while others may be free or on shorter shifts, reducing overtime costs [16].

17. 2.3 Case Study 3: AI-Based Quality Control and Inspection Systems

Artificial intelligence (AI) has shown great potential in manufacturing production for equipment prediction maintenance, process optimization, and quality control (cleaning of defective products) [2]. This study examines AI-based quality control and inspection systems in manufacturing. As manufacturers strive to improve quality and yield while minimizing costs and risks, AI-driven quality control systems that automatically monitor manufacturing conditions and determine the quality of manufactured products can be promising alternatives to traditional systems. This work surveys AI implementations in quality control and inspection throughout the entire manufacturing process.

Advances in AI, particularly neural networks, are fundamentally changing the landscape of quality control and inspection systems. AI-based solutions, including deep learning, fuzzy neural networks, and hybrid models, can enhance product quality and process efficiency in manufacturing. AI-based quality control and inspection systems can prevent defective products from being shipped, represent promising alternatives to traditional quality monitoring methods and automated inspection systems, and are essential in rising smart manufacturing environments [18]. Quality control systems can determine the quality of products based on manufacturing conditions, while inspection systems can categorize and identify defects in video or image data of products after manufacturing.

18. 2.4 Case Study 4: AI-Enabled Safety Monitoring and Compliance

Manufacturing facilities are working to ensure that AI-enabled safety monitoring systems can continuously monitor workplace activities and identify compliance violations in real-time to mitigate workplace hazards in a timely manner [2]. Such monitoring systems can generate alerts or notifications in writing or audio to inform workers of the violations detected in real-time and develop actions to remediate them. The need for AI-enabled monitoring systems arises from the inability of many organizations to conduct effective workplace inspections due to inadequate resources, vast production surfaces, and the labor intensity, routine nature, and low analytical value of the audits currently in use. The main objective in the design of AI procedures for such safety monitoring systems is to ensure high detection reliability of the violations relevant to significant workplace hazards while filtering out false alarms as much as is feasible [7]. For this purpose, several cases were developed in this research.

The first case involves the recognition of workers without personal protection equipment in a coal mining facility. Such violations are significant, as cases in which workers conduct mining operations without individual protection can lead to irreversible consequences for their health and even fatalities. Seven types of headwear protecting workers from rock falls were used at the facility involved. The second case, developed in collaboration with manufacturing companies producing automotive components, concerns individuals in dangerous professional situations. This monitoring system is developed to recognize compliance violations for manufacturing operations on metal surfaces conducted with uncovered hands, unaccompanied workers on the machining surface of the operation, and workers without goggles safety glasses on laser cutting operations.

19. 2.5 Case Study 5: AI Applications in Supply Chain Optimization

This case study elucidates the AI applications that have been deployed on the SC to optimize SC processes. Within the manufacturing industry, complex end-to-end supply chains (SCs) are often perceived as a challenge with optimization potentials [19]. With the persistent availability of SC-related data, AI-based solutions are appropriate to support the complex optimization of SCs. This case study sheds light on specific AI applications deployed on the SC to support workloads and thereby seeks to provide insights into increasing workforce optimization.

AI considers a similar approach as computational intelligence but pursues a more holistic view that includes aspects beyond pure algorithms and modeling. On the one hand, AI focuses more on mimicking human behavior by developing machines that can exhibit some level of intelligence [1]. Currently, the term "AI" is often marked by the emergence of machine learning (ML), i.e., applications that learn from data (data-driven models). In contrast, computational intelligence encompasses sophisticated but traditional algorithm-based heuristics such as genetic algorithms, fuzzy logic, artificial neural networks, etc. (such paradigms are still avoided in ML).

20. Conclusion and Future Directions in AI-Based Workforce Optimization

The enterprise of American manufacturing hinges on a highly skilled workforce who possess competencies in operative teamwork and problem-solving. As the demand for advanced and smart products grows, personnel must be trained effectively without neglecting contemporaneous output expectations. Such re-tooling, refinement, or upgrading of competency is termed workforce optimization. This challenge, also known as "on-the-job training," becomes significantly more involved as the workforce scales. Leverageable process information exists in the manufacturing system datasets (centralized Data Lake concept) from which to utilize data analytics. However, such analysis is often beyond the capability of plant operation. As a remedy, manufacturing-specific artificial intelligence (AI) and machine learning (ML)-based software systems called smart manufacturing platform technology (SMPT) have been developed. While myriad state-of-the-art (SoTA) AI and ML algorithms exist to address specific manufacturing concerns, a set of enterprise-level layer SMPT platform technologies have been developed. Herein, the integration of SMPT and AI/ML technologies towards American whitespace manufacturing workforce optimization is proposed. The necessity of such overall enterprise consideration and effort is illustrated via simulation and a pilot plant case study. The SMPT performance is robust across plants with varying configurations and employ disparate data analytics technologies. A future workforce optimization vision, collectively and broken down by necessary R&D tasks, is also presented [1].

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