The Role of AI-Driven Decision Support Systems in Optimizing U.S. Defense Manufacturing Operations

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1. Introduction to AI-Driven Decision Support Systems

The application of an AI-driven decision support system can be used to help equip planners allocate the precise resources necessary to assist in the completion of manufacturing operations on time, all the time. As a component of the fourth iteration of the Industrial Revolution, these decision support systems, also termed extended reality (XR), are anticipated to provide the United States with an opportunity to revamp traditional manufacturing concepts and improve defense manufacturing operations. XR platforms consolidate real-time data from enterprise resource planning (ERP) and product lifecycle management (PLM) systems, advanced machine communications, and the cloud to report on the performance of one or many defense manufacturing operations.

This data-driven depiction of the manufacturing operation can also serve as the foundation for an AI-driven decision support system that can predict and/or propose improvements or resource modifications to assure on-time delivery of defense products. Robotics and IIIoT components such as sensors, cameras, Morse spindles, local server and more were acquired to develop this version of the platform. Below, we supply an overview of the functional components of the XR platform which serve as the foundation for an AI-driven decision support system. This AI-driven decision support system is the subject of current research. Either explicitly or more likely implicitly, the functional components or their functionalities of an AI-driven decision support system should possess certain defining characteristics for it to be considered a decision support system driven by AI.

1.1. Definition and Components of Decision Support Systems

A decision support system (DSS) is a computer-based information system that helps opponents improve their performance in problem areas by supplying intelligence and new information that is timely and relevant in an organized manner. A decision support system will lead to new initiatives, insights, and actions thanks to its collaborative approach of individuals, technologies, and methods. We could see the DSS as a library. It won't accomplish something until we let our experiences out and then take advantage of the insights available. Driven decision support systems (ADSS) rely on artificial intelligence as a primary component. AI elements might include scripts, professional systems, visual programming, rule-based expert systems, model management systems, model inventory approaches, metamodel generators, fuzzy logic frameworks, algorithms, neural networks, and evolutionary prototypes, among others.

No AI hand-lettered code, all combined, could be considered leaving out AI use in automated machine learning (AutoML). AI is used in these DSSs for a range of purposes, including data maintenance, data retrieval, data validation, and forecasting. Decision support systems are used in state-of-the-art defense manufacturing operations to boost collaboration and decision-making abilities. ADSS use AI to make suggestions to solution providers in order to boost the effectiveness of supporting decision-making processes. AI is a sophisticated decision support mechanism that supports individuals' capacity to make choices. It's critical to let ADSS help resolve problems and make choices in this or new domain. We discuss the pivotal function in decision support systems in defense manufacturing planning operations, and define such devices as AI-enhanced decision support systems.

2. Importance of Optimizing Defense Manufacturing Operations

Defense manufacturing includes the production of automobiles, aircraft, ships, trains, and other durable goods. The manufacturing sector's importance to national defense is high. For aircraft weapon systems, the acquisition cost of manufacturing adds up to about 20% of total life cycle costs. Additionally, combat effectiveness is directly related to precision manufacturing and materials technology. Inefficient manufacturing processes or poor materials can yield sluggish, inaccurate, or even unusable weapon systems. To improve defensive posture, it is critical to optimize defense manufacturing operations to be as efficient and precise as possible. There are many factors that contribute to sluggish defense manufacturing, including part variation, low-volume high-mix operations, lack of digitalization, and production strategies that do not target optimal solutions due to not being able to dig through the entirety of the solution space. This paper outlines how AI can be a tool in the warfighter's arsenal, most importantly in the agile, near-term of Prime Lifecycle Systems (PLS): maintenance, repair, and overhaul (MRO), sustainment, and depot operations.

Despite the importance of defense manufacturing, the U.S. has been far surpassed in manufacturing technology by countries such as Germany, Japan, and China. There are dozens of reasons why our manufacturing technology and defense industrial base has fallen behind. The main research question this paper attempts to address is: How can we increase inefficient defense manufacturing through UP? First, AI can work across the entire solution space. This is an inverse problem to the additively manufactured component, which can exhibit millions of possible laser paths constituting the solution space. AI does not suffer from large constrained solution spaces – in fact, as the number of solution options increases, AI often becomes more accurate. In doing so, AI does not rely on traditional, iterative convergence numerical techniques; it can evaluate entire problems with immediate result. Second, maintenance, repair, and overhaul (MRO) of parts can be highly manual or robotically driven. It is expensive and takes a long time to generate PLC and apply them. Also, due to aggressiveness, work-ready components only represent an initial step in prime lifecycle systems. Although it is less important than generating PLC, the repair process still wallows aimlessly.

2.1. Challenges in U.S. Defense Manufacturing

Unlike the commercial sector, U.S. defense manufacturing is unique in that it requires a significant investment in time and resources to make new products and adopt novel processes. Due to the effort and risks associated with these investments, defense manufacturers tend to be cautious about adopting innovative technologies and processes, especially when they are unsure about the future production schedule of these products. Not surprisingly, only widely accepted technologies and techniques are applied, and once a process is in place it generally remains unchanged. This mindset, while understandable, also means that the majority of defense manufacturing processes are somewhat limited and inefficient because they are older technologies based on older design concepts and possibly older materials and processes. As a result, many of these products are no longer state-of-the-art and do not incorporate the latest advances in materials, processes, or design. The few more advanced programs may benefit from newer technologies, but because of the heavy investments necessary for these technologies, program quantities and materials often remain set at the time they are proposed.

Manufacturing firms must continue production to meet their military needs—affecting protection, diplomacy, and deterrence—despite uncertainty regarding future production levels, workforce skillsets, and corresponding capital investments. Short-term shifts in demand (production, procurement, and fielding) and supply chain risk often create "bullwhips" involving military impact (combat readiness and/or cost). The limitations of traditional optimization methods confined solutions within "small final-value neighborhoods," creating impractically large optimal inventory positions. Although Small Business Innovation Research (SBIR) topics explore relevant concepts in analytics and forecasting for industrial base investment, military impact studies are missing. Given the cost and time investment necessary to make substantive changes, investment forecasts must have an even longer horizon than commercial forecasts, which can be no longer than five years in advance in the private sector.

3. AI Techniques for Decision Support Systems

AI offers several interrelated techniques for building DSS, such as machine learning, knowledge-based expert systems, decision trees, fuzzy logic, genetic algorithms, and neuro-computing systems. It is important to note that no single AI capability is sufficient for complex tasks faced by defense system managers. For the purposes of examining AI capabilities with interest in U.S. defense-related manufacturing, machine learning is a promising branch of AI. The knowledge for machine learning systems is derived from the data available at the Air Force plant and should lead to AI-aided decision makers applying that knowledge to obtain some mix of more efficient, effective, flexible, lower-cost, and high-quality manufacturing systems capable of responding to expected changes and crises in strategic and tactical defense-related planning.

Machine learning is one of the application domains of AI. It has its roots in a branch of AI called pattern recognition and has been primarily developed to (i) automatically look through large volumes of raw data to find relevant and meaningful information, and (ii) use that information to make predictions, classify situations, or make decisions based on that understanding. It relies on sophisticated data preprocessing, and its main application is to enable making better decisions in complex situations where limitless streams of data are being generated. There are different pitfalls to be aware of when using machine learning algorithms, including the possibility of overfitting, training on incomplete datasets, and over-reliance on commonly used datasets. Furthermore, creating training data for ML carries added expenses because of the need for properly labeled training examples.

3.1. Machine Learning Algorithms

Machine learning algorithms can be classified into five main categories: supervised learning, semi-supervised learning, unsupervised learning, self-supervised learning, and reinforcement learning. Reinforcement learning focuses on the concept of agents interacting in the environment with the aim of learning a policy ensuring maximal rewards due to the actual states the system finds itself in. The optimization of this framework can use several methods, for instance, determining which actions are considered better than the others for a given state.

This system has multiple possible applications and can be trained through many different methods such as TD learning (Sarsa, Q-Learning, Deep-Q Networks), or policy gradients (rewards given by the analysis of state-to-state dynamics). However, despite the enormous research investment, practical optimization effectiveness is not as high as state-of-the-art deep learning for supervised learning applications. But, reinforcement learning has one significant advantage over other classes of AI, mainly for interactive settings.

RL can handle any learning environment given by a varying degree of observability, for instance, Markovian decision processes (fully observable and stateless) and partially observable (non-Markovian) decision processes. However, LEO parameters are not perfectly known, for example, there are uncertainties about the type of the optimal manufacturing model among Island modeling. The majority of these uncertainties concern the best way to encode the states of the environment, reward signals, etc. AI-driven decision support systems were created using RL algorithms due to their capacity to effectively navigate the uncertainty without perfect previous data availability. It also learns over time the best actions and policies for the best outcomes when the future is uncertain.

4. Applications of AI in Defense Manufacturing Operations

Artificial intelligence, and in particular machine learning, is increasingly being applied to defense manufacturing operations in the job shop setting. The typical stated goal of these applications is to optimize, in some fashion, the operations themselves. These applications can result in fewer changeovers on a machine, enable tasks to be finished more quickly, or result in overall minimized consumption of resources. They also have applications beyond just the optimization of production operations. Beyond the area of defense operations, predictive maintenance has seen probably the most widespread application of AI in the defense industry. Machine learning and AI more broadly are used in defense to optimize other stock levels in addition to predicting maintenance work.

Most, if not all, of the applications are not standalone systems. Instead, they are supportive components that require human interaction or additional software to complete the application. The benefit of their application is easy to see. They all lead to some savings in time and money. Perhaps most interesting is that these applications can have iterative improvement on the operations themselves that they are integrated into. In predictive maintenance, not only are costs saved by not replacing components that don't need replacing, but tied to that are costs saved by disruption to vehicles being lessened. For instance, downtime of a vehicle in maintenance is shortened, leading to more vehicle operation time and less vehicle needed to perform the same task. This concept can be extended to aviation and use the term sorties.

4.1. Predictive Maintenance

As mentioned previously, predictive maintenance involves "the scientific technique of monitoring the use case of a piece of equipment, and then using historical data to predict when the equipment might fail or require a fix." While machines break for a variety of reasons, wear and tear to mechanical parts is often the culprit. AI and machine learning can use the manufacturing data that the DoD captures as part of their systemic analysis to be better than reactive and preventative maintenance methods. Rather, a system of system advanced analytics enables the prediction of wear and tear to help maintain equipment at peak performance. It is not surprising that predictive maintenance should be a significant AI application for the DoD.

The U.S. Navy and Air Force currently struggle to deliver specifications mandating maintenance intervals that are linear with cost when it comes to their most advanced engineering equipment. "Similar to a maintenance program for a car, most commercial equipment manufacturers specify inspection and maintenance [of aircraft parts] based on the number of operating hours," says Lt. Alexander Mamikonian of Naval Station Norfolk. "However, a maintenance program for a car does not involve a jet engine costing $10 million with components that require a restoration process at over $1 million. Hence, we must do the restoration before the component fails." Therefore, restoration is conducted not only at regular CAGR-based intervals required for a cost-effective maintenance program, but also earlier based on component performance trends and operational use.

5. Integration of AI-Driven Decision Support Systems in Defense Manufacturing

Introduction Defense manufacturing has an increasing interest in improving production operations by leveraging data science tools found in artificial intelligence (AI), specifically AI-driven decision support systems that can optimize such operations. Defense manufacturing includes factories that produce items such as communications and intelligence systems and aircraft, but the tools, systems, data, and processes to do so are typically secret, so it is difficult to share specific AI results. Consequently, we explore in this report some of the considerations and complexities involved in employing AI-driven decision support systems in high-tech production of components to systems in the U.S. defense sector.

The integration of AI-driven decision support systems within defense manufacturing, as well as many other types of manufacturing, is complex, multifaceted, and multi-stakeholder. Furthermore, by leveraging existing or emerging AI capabilities, defense manufacturing is reducing an already small pool of technologies that can be shared with non-defense manufacturing. Additionally, using AI for systems -- for example, aircraft systems, communication systems, sensors, or missiles, and their complex systems of systems -- raises unique questions and issues. It is vitally important to capitalize on our technological edge to optimize defense logistics -- especially relying on commercially hidden defense -- yet navigating these concerns is multidimensional. There is a public perception dimension and questions about gain offsets previously held in near-taboo status. For example, do we employ AI for defense later in production, increasing the investment and time to fill the pipeline, versus the potential benefit of costs and schedule associated with changes farther along in the production chain?

5.1. Challenges and Considerations

The previous section has presented the meaning that AI technology can bring in a positive context in the defense manufacturing concern. The greater reliance on AI-driven decision support calls for several challenges and considerations that should be taken into account. Several are peculiar to the domain of defense manufacturing concern, which can result in a somewhat more complex definition of the relevant business cases for adopting this technology, restricted as these LPs can be. The vague implications in regard to defense manufacturers can also result in cautious consideration around the implementation strategy and change management aspects specific to the introduction of AI/ML-driven decision making.

A military system is usually developed and procured in low volume, over a long period, with each step heavily reliant on the output of the previous step. Defense sustainment in the context of this study represents support from the end of development through to the prime contract with the defense organizations to "provide for the maintenance, repair, overhaul, modernization of defense systems, and for provision of spare parts, logistical support services and technical service." The below aspects relating to defense manufacturing and how they affect the adoption profile of AI technology were gleaned from official documents published by the U.S. DoD and interviews with staff currently active in defense manufacturing across three defense organizations. These considerations form the considerations of the MCDA decision model, described in section 6.3 of this paper.

An AI system developed with DRL can often not explain the reason for their decisions. Often these systems make choices based on historic or symbolic reasons that bear a low or undefined correlation with the present set of circumstances. JASON is a U.S. DoD organization, initiated in 1999 to ensure utility and scientific validity.

6. Case Studies and Success Stories

Case studies and success stories: Several illustrative case studies and success stories exist that demonstrate the utility of AI-driven decision support systems in the U.S. defense manufacturing operations space. For example, IBM created an AI-based assistant for a group of engineers working in collaboration centers called "Garages," providing cognitive insights based on vast amounts of structured and unstructured data collected about a given vehicle. IBM Watson, the umbrella technology that delivered the AI capabilities, uses natural language processing and machine learning to reveal and generate previously hidden critical insights, patterns, and relationships in data. This translates into speed, resolution, and precision that would have otherwise required time-consuming, manual analysis, reducing the time taken to analyze and develop systems with a significance that spans product-related imagining to aftermarket support for customers. AI engineers working with the Garages began to use the AI appendage to "tune in" to factors, processes, and systems that correlated with, or would drive, outcomes.

In another study, the manufacturer used AI to predict which supply build processes would correlate to good vs. bad performance. These systems are like invaluable coaches that can see around invisible corners using data, giving information, experience, and insights to improve your performance from minor tweaks to fundamental changes. Additionally, the Department of Defense has conducted multiple exercises, war games, and analyses that concluded AI would be crucial to maintaining U.S. military dominance in future conflicts. One such self-described "US Air Force gaming organization" presented a scenario where a U.S. Air Force commander is fighting a peer competitor and is getting overwhelmed with data. The key to winning, according to the war game, is to actually reduce the number of people and speed up decision-making through AI-driven decision support. This demonstrates the utility and emphasis of AI tools in war games. Essentially, the desired outcome is to improve the speed, quality, and accuracy of decision-making through the decision support.

6.1. Implementation in U.S. Defense Industry

Implementation of AI-driven decision support systems in the U.S. defense industry

Example 1: AI-driven demand forecasting for spares Client: U.S. Army Financial Management, BETSS-C Program Strategic Objective: The federal government must maintain adequate supplies through near-term mitigation efforts during revenue reductions due to disasters or changing markets, and respond to protracted conflicts or global security threats. Immediate Outcome: Increased effectiveness of SRM analysis and decision-making on system and system component supply chain resiliency. BIAMP deliverable: Costly overstock prevention through enhanced forecasts relative to historical ordering behavior, driving end item stocks down 67 percent of overstock.

Example 2: AI-driven production planning and scheduling Client: Siemens Government Technologies, a service-disabled company Strategic Objective: Optimize supply chain throughput, efficiency, and sustainability through cost-efficient AI-driven applications. Immediate Outcome: Increased production throughput by more than 100% for energy supplying and performing manufacturer due to accelerated repair of gas turbines. BIAMP deliverable: Optimized production by NSA repair and return asset value of C-130J aircraft engines to address current and forecasted C-130J maintenance engineering, supply chain, and disposal constraints. Execution Method: A hybrid analytics approach leveraged descriptive analytics, simulation, optimization, and prescriptive analytics. A dashboard for decision support for the hardware repair process highlighted core findings and processes.

Potential Follow-On AI Applications in the Defense Industry As depicted in Figure 9, other AI-supported decision-making systems can be developed within the U.S. defense industry to reduce equipment availability issues and to complement smart manufacturing and IoT capabilities. The application of AI-ReSS can help inform strategy relative to current and potential contracts and optimize the use of resources, personnel, and future technologies, and the AI-Classification system can help defense programs and financial management personnel to better estimate ongoing O&S costs. In addition to the examples we presented in previous sections, we are able to demonstrate the high-level potential return on investment of these AI applications. We have verbal transfer of information rights from our federal clients to share.

7. Future Trends and Innovations

The improved AI approaches are already driving dramatic performance improvements in many domains, and decision support systems in defense manufacturing are likely to benefit as the field continues to advance. AI nanotechnology development enables the production of successively more powerful computers through the application of a series of smaller, faster substitutes. This trend has historically shown a roughly 10× improvement every four years. Hypothetical point-of-deployment AI will be used for decision support at the neural, intermediate neural, and molecular levels. Military systems build subsequent developmental nodes in this progression will be fielded, ensuring technological advantages over A2/AD forces.

The development of DECMAI tools capable of functioning in A2/AD environments will continue beyond the conventional applications of decision support systems. The progress of AI-related responses and attacks will continue to exceed current predictive models' ability to account for them. This also ensures that learning- and reinforcement-based AI systems will be an important part of decision support system research. AI systems have the potential to be trustworthy and deployable in the defense industry. AI has great potential across the production life cycles. While manufacturing is showing utilization, AI has the potential to improve everything from design to production.

7.1. Advancements in AI Technologies

Funding for AI research continues to increase. Some of the most lucrative straight-A AI firms include those with a primary focus on the military. Contract support for fair AI research has also taken off, focusing specifically on military applications. According to work by researchers with the Project on Government Oversight, amounts obligated for contracts focused on AI in the defense and national security context more than doubled each year from FY 2017 to 2020. In FY 2017, top contractor investment was in data processing and software. It shifted primarily to research and development in FY 2018, with an increasing investment in services and a surge in investment in those services in FY 2020.

The cumulative effect of investment has been substantive, with the quality and immersive capabilities of AI technologies continuing to increase and evolve. Today, AI is evolving from its traditional role as a tool to increase human capabilities to an advanced, multi-component technology that can simulate, or in some cases manifest, human-like perceptual, cognitive, and physical abilities. Robust technology development is shedding new light on questions of operationalizing the use of AI robustly and safely in defense contexts—interactive contexts characterized by complexity, uncertainty, and extensive use of humanops and human-in-the-loop (HITL) systems. With that in mind, we posit that AI-driven DSSs will be able to incorporate this knowledge to become substantive contributors to DoD defense manufacturing and strategic capacity in the future. We aim to describe the creation, experimental validation, and theory-practice alignment of socio-technical systems that have the goal of addressing both. Tapping foundational scientific principles, we are interested in understanding the design space of what can be accomplished by these interactive DSSs when considering the potential upgrade, side, and other effects including HCI/HRI concerns such as user workload, acceptance, and believability associated with human-AI interactions.

8. Ethical and Security Implications

The lack of appropriate security and privacy measures might lead to data breaches and adversaries being able to steal the proprietary, classified manufacturing data. Data privacy is a large concern for manufacturers and military systems. It would be unethical to base critical decisions off third, fourth or even seventh parties' data without their explicit approval. Just because data are deemed 'public' does not mean they are fair game. There are cultural and socioeconomic factors to consider when harvesting data from citizens and organizations in other countries. We should assume that the U.S. defense manufacturing enterprise is the largest and most prosperous in the world and should not need to borrow data to make appropriate decisions. Giving decision making for U.S. DoD systems/operations to foreign minds or entities is in and of itself unethical and carries significant security concerns.

This is not specific to AI but as we move from humans to early stage AI, Industry 3.0 to AI driven decision support we need to consider ethical considerations in play, and then as we move to full autonomy (to include shaping, thinking, and acting), we need to consider and review those that were considered early on including: Informed consent vs. third party data use and consent, Data subject rights and corporate responsibility, Ownership, Trade, agent, and state, Smart manufacturing and labor issues, and Accountability and decision support. Mandatory legal language needs to be presented and written into the purification process that informs all participants of the AI intention. Formal consensus from decision making authorities is needed to incur and review/ consider acceptance of the law. The government or an oversight committee is responsible to hold those "self-regulated companies" accountable for the fairness of AI. Financial sanctions are necessary to ensure compliance. Clear dispute and conflict processing are necessary for their daily adoption and execution in the workplace.

8.1. Data Privacy and Security Concerns

8.1.1. Ethical Implications

Data privacy and security concerns are rooted in the ethical component of concerns. Specifically, institutions may make use of AI to develop decision support systems that assist with many of the functions mentioned in previous literature, but many still argue that human intervention will always be required as the final decision-maker when it comes to issues like warfare. However, many of the tasks supported by AI decision management and planning assistance require the exchange of highly sensitive information, including classified information. Using AI to make those decisions and share classified data brings a host of new challenges with it, including issues like data privacy and security. Additionally, the rise of any kind of AI introduces ethical challenges like those around dehumanization. These potential dysfunctions are made all the more likely by the introduction of new and speculative offensive AI-enabled systems operating in such a complex and globalized ecosystem.

8.1.2. Mitigating Risks

Vague threats underscore the importance of robust measures for nothing else than injury prevention. Most relevantly to this study, discussions of the potential threats associated with the use of AI in military settings underscore that even systems untouched by malevolent actors offer some opportunities for new interference and influence. This paper seeks to address a potential point of interest in AI that is exposed by discussing criticisms of AI decision support, however, with a new subject of scrutiny: the way that AI might change the outside challenges when applied as sensor-augmented decision support systems in all military and business functions. Such systems are widely feared for the very real possibility of threatening existing defensive operations, and are thus also of identically real interest to attackers and offensive users, not least in the commercial sector. As Craig and Kramer (2003, pp. 88) warn, 'a growing percentage of all serious attacks...stem from economically motivated extortion plots.' In addition to enhancing cybersecurity, they further argue that attackers often only require 'one small breach to protect their time and (often large) monetary investment', suggesting a certain ease of execution on a larger industrial base, rather than simply on larger and high-profile targets.

9. Conclusion and Recommendations

In the last few years, manufacturing in the context of the U.S. Department of Defense has been transitioning towards a predominantly digital-driven perspective. This paper examined the application of advanced artificial intelligence (AI) driven decision support systems to improve decision-making within the defense manufacturing domain. Real world challenges and impacts were discussed along with potential solutions for transitioning from a limited scope stand-alone testbed to a robust decision support system operating across the U.S. Air Force's depot system. When the technical solution was insufficient for meeting our desired outcomes, this work became a broader research study conducted in collaboration with defense manufacturing operators to explore the human and task old experiences in-depth. Our findings suggest that as defense manufacturing shifts from a reliance on digital information to a more data-driven world, human operators are experiencing new limitations for making decisions and could benefit from intelligent systems that can help augment their cognitive capabilities.

The research community has seen encouraging results from the development of intelligent systems that improve decision-making. The problems faced by consultants are quite popular in the real world. Currently, the Department of Defense uses many stand-alone AI and machine learning (ML) applications for addressing different operational challenges. Because these are stand-alone applications, there can be contention and operational inefficiencies. Although AI is a topic thoroughly discussed in the industry and especially in areas such as predictive maintenance and logistics, there is a noticeable dearth of research on AI and ML applications that focus on defense manufacturing objectives, particularly when those objectives differ significantly from already well-studied civilian objectives. Given the seminal nature of this research, our implications have been stated in three areas: tactical, literature, and industry.

9.1. Key Takeaways and Future Directions

In presenting the capabilities, acceptance from practitioners, and consequential insights that can be mined through the application of AI-driven decision support systems, this paper lends itself to a variety of reasonable next steps for practitioners, academics, policymakers, and industry. Whether a technologist or a "sweater-vest academic," we hope this paper motivates downstream analysis and proposed actions. For example, a technologist could consider what data would be needed to specifically draw insights that practitioners could systematically grow from. And for academia, members of the policy and defense community could consider what changes need to be implemented in order to more seamlessly integrate these new technologies into the national defense contracting enterprise. Industry, similarly, could ideate how these technologies and research gaps specifically impact commercial manufacturing choices and lean management. Overall, here are a few core insights and future actions that the authors of this piece are considering for CyberMan Enterprise Dynamics in specific, and new predictive control solutions more broadly.

In this paper, the authors presented an extension of a long-standing agent-based simulation tool, CyberMan, to include 'what if' and predictive scenario planning as an embedded feature. This set of decision support tools allows users to rapidly develop scenarios ranging from do-nothing to 'optimal' turning of knobs in the presence of interacting and competing objectives. A validation of the current system was presented in the case of a naval base metalworking center. This model-based decision support system made it clear to decision-makers the magnitude of the complex interactions associated with competing priorities, as well as significantly reducing the decision horizon supporting long-term SayDo analysis. These results held out the potential insights available through future iterations of the tools as the model becomes more deeply intelligent and capable. It is clear that these tools are promising, but until widespread adoption and integration of these technologies are underway, it will not be possible to measure their direct impact in either more rapid decision making or genuine improvements in defense manufacturing efficiency.

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