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From Factory to Field: Modeling Production Capacity and Logistics Effectiveness for Defense System

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From Factory to Field: Modeling Production Capacity and Logistics Effectiveness for Defense System

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Abstract

Recent conflicts have underscored the importance of adaptable supply lines in contested logistics and rapidly evolving technological environments. Traditional supply chains respond slowly to changing conditions and often lack traceability to campaign-level measures of performance. To address this gap, we propose a modeling and simulation (M&S) environment that supports data-driven assessment of alternative scenarios. A previous phase of the effort developed an overall logistics model for the delivery and storage of goods, although that model has not yet been fully integrated with the present work. This paper focuses on a higher-fidelity model of a notional manufacturing facility and evaluates how production-line design changes affect campaign-level supply-chain performance. The manufacturing steps are based on publicly available descriptions of Ling-Temco-Vought's Multiple Launch Rocket System production process. Two scenarios are examined: a battle scenario that transitions from high-demand engagement to lower-demand sustainment and a second scenario that introduces an unexpected surge in demand.

Introduction

Military logistics has emerged as a critical capability for the United States as it prepares to compete with near-peer adversaries. Although frontline platforms often receive the most attention and investment, sustaining those forces over time remains a persistent challenge. Recent efforts to supply Ukraine have highlighted vulnerabilities in the Defense Industrial Base (DIB) on which U.S. forces would depend in a large-scale conflict. Supporting a modern fighting force requires long production lead times, early contractual commitments, and clear visibility into demand across the entire supply chain, from the factory floor to the point of use in theater. More broadly, the current era of Great Power Competition is forcing a reassessment of DIB readiness. As noted in the NDIA & DRIVE Contested Logistics Workshops Summary & Recommendations, "The readiness of the U.S. defense enterprise to sustain potential & prolonged conflicts is increasingly a concern" (National Defense Industrial Association [NDIA], 2025). In this context, the DIB must evolve into a threat-informed defense ecosystem that can scale production, satisfy surge demand, and recover during a major conflict. Among the resulting recommendations, improvement in manufacturing planning and execution stands out as a clear priority.

This research investigates how manufacturing capacity for a missile launcher affects the ability to satisfy demand across different conflict intensities and tempos. The effort has three objectives: (1) develop a digital modeling environment for launcher manufacturability and production-capacity analysis, (2) conduct sensitivity analyses to determine how process parameters, including machine capacity, affect throughput, and (3) quantify how alternative factory configurations influence the ability to meet specific demand signals.

The Background and Methodology sections first describe the broader factory-to-field modeling effort and the architecture that links demand, logistics, and production. The remainder of the paper focuses on the manufacturing-facility model developed in this phase, the surrogate-modeling approach used to analyze it, and the resulting implications for production-capacity planning.

Background

The overall effort couples logistics and production-system models to create a factory-to-field simulation environment. At the highest level, the logistics model is intended to evaluate supply and transportation capacity, determine how those factors affect mission outcomes, and identify the variables that most improve mission completion. Discrete-event simulation has been widely used for this purpose. Cantrell et al. (2025) used a discrete-event simulation to assess the impact of digital twins under conditions of part degradation, changing conflict intensity, and varying resupply or repair availability. Hoem et al. (2025) examined the effect of predictive-maintenance technologies enabled by digital twins by building a discrete-event simulation of an aircraft logistics system. Metcalf and Laffey (2023) proposed a digital-twin–enabled decision-support system for wargaming and demonstrated the value of such models for what-if analysis when assessing technology or strategy infusions. Paksoy et al. (2012) developed a nonlinear mixed-integer model that integrates supply-chain design and factory line balancing; however, their formulation assumes deterministic parameters and constant demand throughout the scenario.

The overall logistics system is composed of multiple interacting facilities. Because the long-term goal is to simulate the production-to-field process, appropriate factory representation and evaluation methods are also needed. This aspect is directly informed by the work presented in Sieldak et al. (2018), Pinon Fischer et al. (2022), Siedlak et al. (2015), and Libby et al. (2017).

Methodology

This section presents the methodology used to evaluate how manufacturing capacity influences the ability of the broader supply chain to satisfy operational demand. The overall approach links demand, logistics, and production models within a common simulation environment, while the present work focuses specifically on the manufacturing facility component. To support this analysis, manufacturing process times are estimated in SEER-MFG® and then incorporated into a SIMIO® discrete-event model to assess throughput, bottlenecks, and the effects of alternative factory configurations under different demand conditions.

Proposed Architecture of the Overall Environment

To gain full visibility into demand across the supply chain, three integrated modeling capabilities are required, as shown in Figure 1: a demand simulation (or battle simulation) to forecast material drawdowns and delivery locations, a logistics simulation to assess transportation capacity and warehouse status across the theater, and a manufacturing or production model to estimate throughput. Integrating these models enables end-to-end analysis of the supply chain and supports the adjustments needed to meet operational demand. The overall approach is shown in Figure 2.

The logistics simulation environment was established in prior work (Birbasov et al., 2025). The present effort focuses on developing the manufacturing-process and production-facility models needed to estimate throughput for alternative factory configurations. Specifically, the study models the steps involved in manufacturing the Ling-Temco-Vought (LTV) Multiple Launch Rocket System (MLRS®) using publicly available information on the production process (LTV Aerospace and Defense, n.d.). Processing times for the relevant manufacturing activities are estimated in SEER-MFG, while the factory floor, including the type and number of machines, is modeled in Simulation Modeling framework based on Intelligent Objects (SIMIO), a discrete-event simulation environment, to estimate resulting throughput.

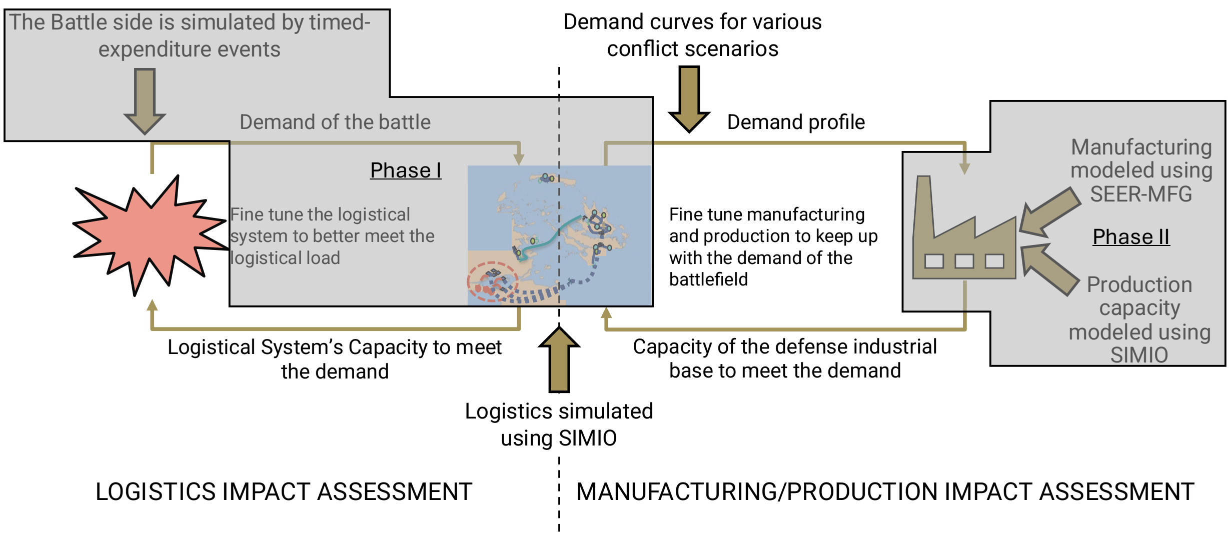

Figure 1. The Overall Proposed Environment. The grey boxes show work done during Phase I and Phase II of the implementation.

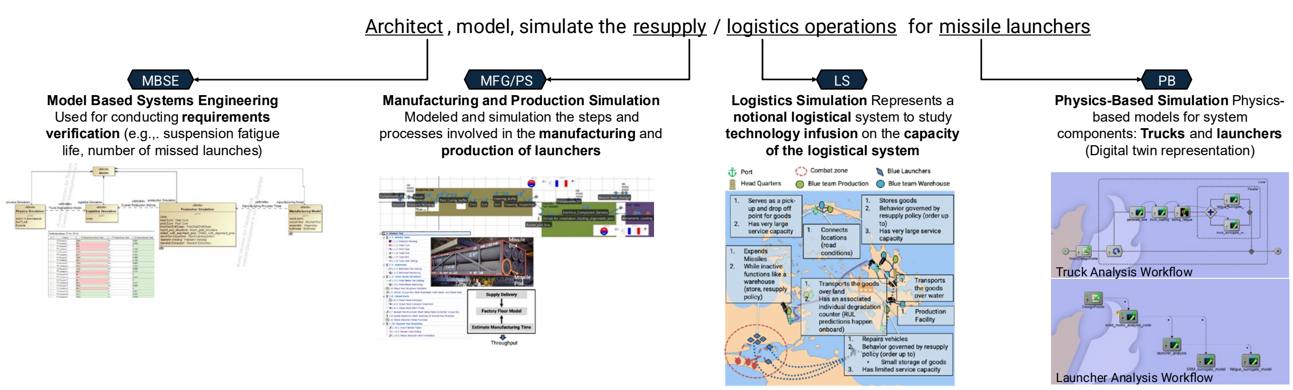

Figure 2. The Overall Simulation Approach Steps

The following sections detail the development of the manufacturing model and the creation of the production model.

Manufacturing Model

This section explains how process-level manufacturing estimates are generated and then translated into a factory-level simulation. Together, the SEER-MFG and SIMIO models provide the analytical link between part design, facility configuration, and production throughput.

Manufacturing Process Modeling

Manufacturing processes are modeled in SEER-MFG (Galorath, n.d.) to estimate the time required for each activity on the production line. Each manufacturing activity is represented in SEER-MFG with its own set of parameters, such as material, geometry, hole count, and machining details. Users can modify these inputs and run the model to obtain process-time estimates derived from a historical database of manufacturer data. In this work, the complete production line is represented in SEER-MFG.

Not all parameters are specified directly by the user. Any inputs that are not explicitly modified are populated by the software's knowledge bases, which are derived from a database of commercial manufacturing processes. These knowledge bases function as process templates that assign values to the remaining parameters within each activity. For example, the composite-manufacturing module includes a filament-winding knowledge base, which is used here to define the filament-winding step.

This work evaluates how changes in selected design variables affect process times and, in turn, downstream logistics performance. In particular, the study varies missile-tube geometry and missile-tube material, then runs SEER-MFG to estimate the process time for each geometry-material combination. The full set of input parameters is listed in Table 1.

Table 1. SEER-MFG Input Parameters

Parameter	Input(s)
Missile Tube Geometry	Diameter [in]
	Length [in]
	Thickness [in]
Missile Tube Material	Fiber Filament
	Weight [lb]

These parameters are used to edit a set of input files for each manufacturing process. Templates for these files are obtained by exporting commands to run the model from SEER-MFG as text files, which are edited with user parameters to create the input files.

SEER-MFG is executed in server mode to automate batch runs. A wrapper script launches the software and continuously queries SEER-MFG for process-time results over a set of input values. This automation supports a design of experiments that captures how process times vary with tube geometry, material, and weight. The procedure is summarized in Figure 3.

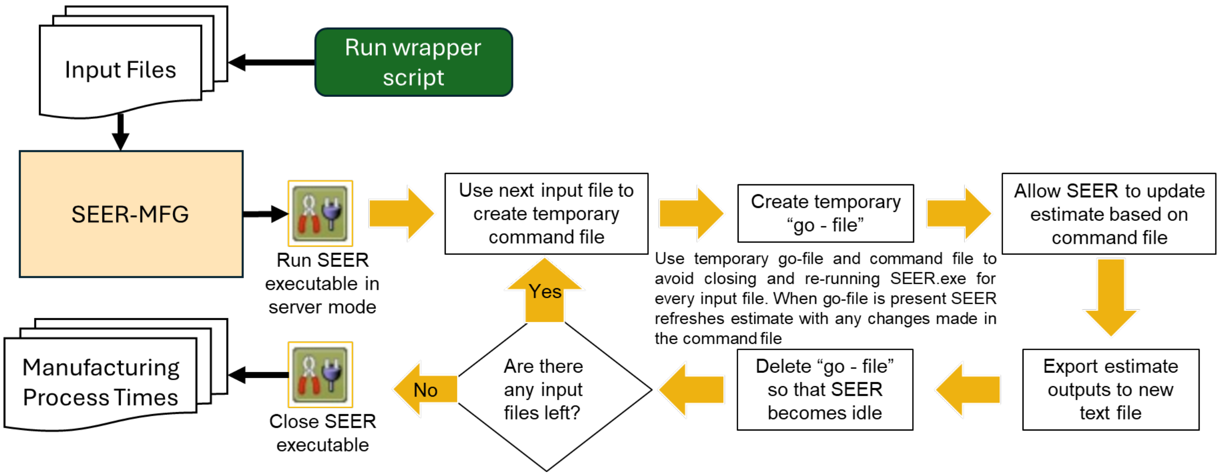

Figure 3. Process of Running SEER-MFG Through Server Mode

Once all runs are complete, the resulting manufacturing-process times can be passed to the factory model to assess their effects on overall production throughput.

Factory Modeling

The purpose of the factory (production) model is to represent a notional manufacturing system in which users can test how technology infusions and factory-floor adjustments affect the industrial base's ability to meet demand. As noted above, the factory model is implemented in SIMIO. SIMIO is an object-based modeling platform that can be extended to multiple paradigms, including agent-based, discrete-event, and continuous simulation. In SIMIO, each object is defined by processes, events, and tables that govern its behavior. The following subsections describe the model elements, along with the logic used to represent production steps and supply deliveries.

The first general assumption is that manufacturing tools and machines do not degrade over time; accordingly, production stoppages due to equipment failures are not modeled.

The second general assumption is that sufficient labor is always available for the planned production shifts.

The third assumption is that the factory operates continuously, 24 hours per day and 7 days per week, without interruptions due to shift changes.

Each subsection below follows a similar format: discussion of the desired modeling task, assumptions, and implementation logic.

The Production Floor

The production floor was based on publicly available information about LTV's MLRS manufacturing facility. Because detailed data on building size and the space required for each production step were not available, a notional facility was constructed using the manufacturing steps identified for LTV's production floor. The resulting layout includes a rocket-pod production line, an assembly line, and an armament-loading line, as summarized in Table 2.

Table 2. Manufacturing Steps

Rocket Pod Line	Assembly Line	Armament Loading Line
1. Filament Winding 2. Heat Curing 3. Forming Mandrel Extraction 4. Post Curing Oven 5. Trim 6. Slot 7. Drill 8. Cleaning 9. Inspection	1. Insertion of Pods into a Structure 2. Installation of Holding Alignment Pins 3. Electrical Component Installation 4. Electrical Inspection	1. Loading Missiles into the Assembled Pod Structures

Each manufacturing step is modeled in SIMIO using server objects. Each object defines the processing time, the number of components that can be handled in parallel, and the associated manufacturing process. Processing times are imported from SEER-MFG, and the mapping between SEER and SIMIO is shown in Table 3. In some cases, several SIMIO steps are represented by a single SEER process; for example, activities such as cleaning and inspection are included within broader SEER manufacturing steps. Because the factory layout is notional, components are assumed to move between stations without internal transportation constraints.

Table 3. SIMIO to SEER Mapping

Manufacturing step in SIMIO	Manufacturing step in SEER
Filament Winding	Filament Winding
Heat Curing Post Curing Oven Forming Mandrel Extraction	Heat Cure
Trim	Tube Trim
Slot	Tube Slot
Drill	Tube Hole Drilling
Cleaning Inspection Electrical Inspection	Accounted for in the other manufacturing steps
Insertion of Pods into a Structure	Center Torque Box Assembly Shock Absorber Skid Installation Bulkhead Die Casting Bulkhead Machining Hoist Beam Die Casting Hoist Beam machining
Installation of Holding Alignment Pins	Missile Tube Drilling
Electrical Component Installation	Electrical Assembly
Armament Loading	Insert Missiles

Each manufacturing step also assigns a quality outcome to the part. This assignment is Boolean: A value of *True* indicates that the part passes the associated inspection, while *False* indicates failure. Parts that fail inspection are removed from the line and are assumed not to be recycled or reworked. Each manufacturing process has its own SIMIO quality-assignment routine, which samples part quality from a normal distribution, $N(\mu, \sigma)$. The user specifies the allowable tolerance by defining how many standard deviations from the mean are acceptable. Each step is assumed to have infinite queue capacity, so parts can accumulate while waiting to be processed; under the scenarios tested, queue lengths typically remain below 10 components. When a step has a fixed batch-processing capacity, parts wait until the required batch size is reached before processing begins. This is especially relevant for heat curing, post-curing, and cleaning. For example, if an oven can process four pods at a time, the system waits until four pods are available in the queue. In SIMIO, this batching logic is represented with a *Combiner*, which merges multiple components into a single entity for processing, and a *Separator*, which disaggregates the entity after processing. This interaction is illustrated in Figure 4.

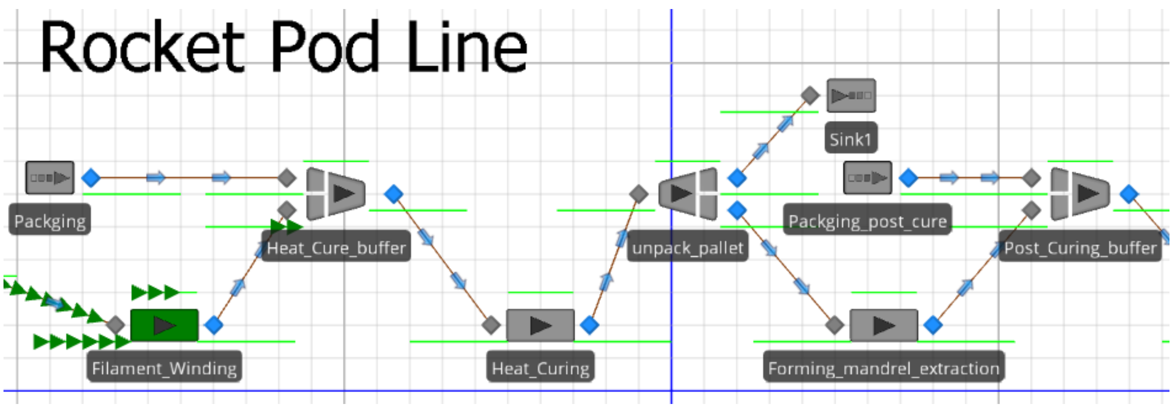

Figure 4. SIMIO Process, Combiners and Separators

Supply Deliveries

Certain manufacturing steps rely on components supplied by external manufacturers. In the current simulation, external supplies are delivered at three key stages: filament winding, electrical-component installation, and armament loading. These inputs are managed through a combination of on-hand inventory and a virtual manufacturing hub from which additional stock can be ordered.

External-component inventory is modeled using SIMIO's *Inventory* element. The element is configured with parameters that define storage capacity, resupply policy, and the resupply process. The current resupply policy is governed primarily by a threshold for replenishment and a threshold for reorder. When inventory falls to the replenishment threshold, a replenishment process is triggered to restock the warehouse.

Orders are placed with an external supplier that produces the requested quantity of goods. Although the supplier and its location relative to the manufacturing facility are not modeled explicitly, delivery time is treated as an input parameter. Users can specify nominal delivery durations as well as potential disruptions using two variables: delay frequency and a multiplier that increases the baseline delivery time when a delay occurs.

Results and Discussion

This section evaluates the simulation-driven environment developed to optimize production throughput in a notional missile-manufacturing facility. The objective is to assess the system's responsiveness to changing operational demand through two mission-based scenarios. The first scenario assumes advance knowledge and sufficient preparation time, allowing the production floor to be adjusted to meet specified end-state inventory constraints. The second introduces uncertainty and implementation delays, highlighting the challenges of adapting late to increased demand. Both scenarios use surrogate modeling to explore design changes efficiently and identify key production bottlenecks for capacity planning and operational decision-making.

Experimental Set Up

The objective of this work is to demonstrate the modeling environment's ability to evaluate factory-floor performance under alternative demand and resource conditions. Because the model is parametric, the number of manufacturing machines or workstations can be varied to examine the corresponding effects on throughput and production capacity. In the absence of a defined real-world layout, a notional factory floor is used as the baseline. The analysis is designed to address two questions: *(1) whether a production facility can satisfy the requirements of a given engagement scenario under a predicted expenditure profile* and *(2) how changes in available manufacturing resources influence that capability when the baseline configuration is insufficient*. To illustrate this approach, two scenarios are examined. Scenario One considers the case in which full planning time is available before mission start, while Scenario Two examines the consequences of delayed implementation and the time required for resource changes to affect production performance. Both scenarios are based on a notional factory and a notional mission. Throughout the analysis, each missile box is assumed to contain seven pods, and the number of machines on the production line is the only adjustable factor.

Surrogate Modeling

To rapidly explore how changes to the factory floor affect throughput, a surrogate model was developed based on results generated by SIMIO. This approach allows designers to easily visualize and analyze trends in performance improvements resulting from various modifications. To train the surrogate model, 2,000 cases were generated across 34 input variables, with the ranges and parameters detailed in. The artificial neural network (ANN) architecture contains two layers, with five nodes in the first layer and three in the second, and uses the TanH activation function. The resulting model achieved an R-squared value of 0.99.

Table 4. DOE Inputs and Bounds for the 2,000 Case Run

Variable	Min	Max			
Length (in)	108	180			
Diameter (in)	8	10			
Thickness (in)	0.059	0.118			
Material	Silicon Carbide	Glass	Carbon	Armid	Aluminum Oxide
Heat Cure (Capacity)	1	10			
Cleaning Process (Capacity)	1	10			
Filament Winding (Number of Machines)	1	10			
Trimming (Number of Machines)	1	10			
Slot (Number of Machines)	1	10			
Drill (Number of Machines)	1	10			
Inspection (Number of Stations)	1	10			
Pod Insertion (Number of Machines)	1	10			
Assembly Drill (Number of Machines)	1	10			
Electrical Component Installation (Number of Stations)	1	10			
Electrical Component Inspection (Number of Stations)	1	10			
Armament Loading (Number of Machines)	1	10			
Missile Local Storage Initial (Count)	15	100			
Missile Local Storage Green (Fraction)	0.5	1			
Missile Local Storage Yellow (Fraction)	0.2	0.5			
Electrical Local Storage Initial (Count)	15	100			
Electrical Local Storage Green (Fraction)	0.5	1			
Electrical Local Storage Yellow (Fraction)	0.2	0.5			
Filament Winding Local Storage Initial (Count)	15	100			
Filament Winding Local Storage Green (Fraction)	0.5	1			
Filament Winding Local Storage Yellow (Fraction)	0.2	0.5			
Armament Delivery Delay [Normal](Hours)	5	40			
Electrical Component Delivery Delay [Normal](Hours)	5	40			
Filament Winding Delivery Delay [Normal](Hours)	5	40			
Armament Delivery Delay Extra Time of Occurrence (Hours)	0	1200			
Armament Delivery Delay [Extra](Mult)	2	10			
Electrical Component Delivery Delay Extra Time of Occurrence (Hours)	0	1200			
Electrical Component Delivery Delay [Extra](Mult)	2	10			
Filament Winding Delivery Delay Extra Time of Occurrence (Hours)	0	1200			
Filament Winding Delivery Delay [Extra](Mult)	2	10			

Scenarios and Results

Scenario One

In Scenario One, a notional mission was developed consisting of two distinct phases, each characterized by different expenditure rates defined using normal distributions. Phase One represents a high-demand period, while Phase Two reflects a lower demand. Table 5 outlines the detailed breakdown of the scenario. Demand is expressed in terms of missiles per event, and the number of missile boxes required is calculated by dividing the total missile expenditure by seven, the number of missile pods per box. For analysis, the demand data was aggregated into 25-day intervals.

Table 5. Scenario One Break-Down

Variables	Dist(mean,std)	Notes
Scenario: Continuous Battle High		
Time Interval	Normal(7,1) [hours]	Time between launch event
Number of Missiles per Event	Normal(10,3)	
Scenario: Continuous Battle Low		
Time Interval	Normal(8,1) [hours]	Time between launch event
Number of Missiles per Event	Normal(4,1)	

Assuming an initial stockpile of 1,000 missile boxes, Figure 5 illustrates the impact of demand on inventory levels. Under the given notional setup, the stockpile is fully depleted by day 425. For Scenario One, a constraint is imposed requiring that at least 400 missile boxes remain in stock by the end of the mission.

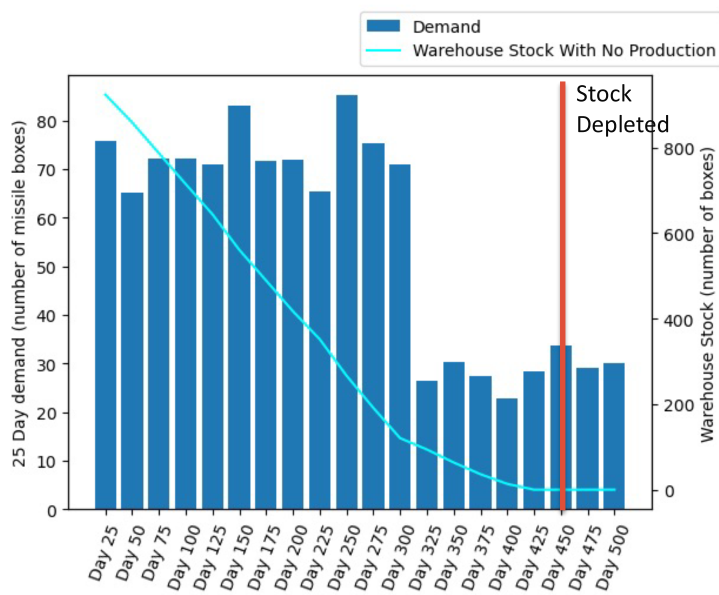

Figure 5. Demand and Warehouse Stock; No Production

As introduced earlier, a notional factory configuration was selected as the baseline. Table 6 summarizes the missile-pod parameters and the corresponding factory configuration.

Table 6. Notional Factory Set-Up

Factory Set Up		**Missile Pod Params**	
Heat cure (capacity)	4	Length (in)	152.37
Post Heat Cure (capacity)	4	Diameter (in)	9.43
Cleaning process (capacity)	2	Thickness (in)	0.1
Filament Winding (machine #)	1	Material	Carbon
Mandrel Extraction (machine #)	1		
Trimming (machine #)	2		
Slot (machine #)	5		
Drill (machine #)	6		
Inspecting (station #)	4		
Pod insertion (machine #)	1		
Drill assembly (machine #)	5		
Electrical components install (machine #)	7		
Assembly inspection (station #)	1		
Armament loading (machine #)	4		

Figure 6 shows the performance of the notional factory configuration under the mission described above. This configuration yields a throughput of 6.2 missile boxes per 25-day period.

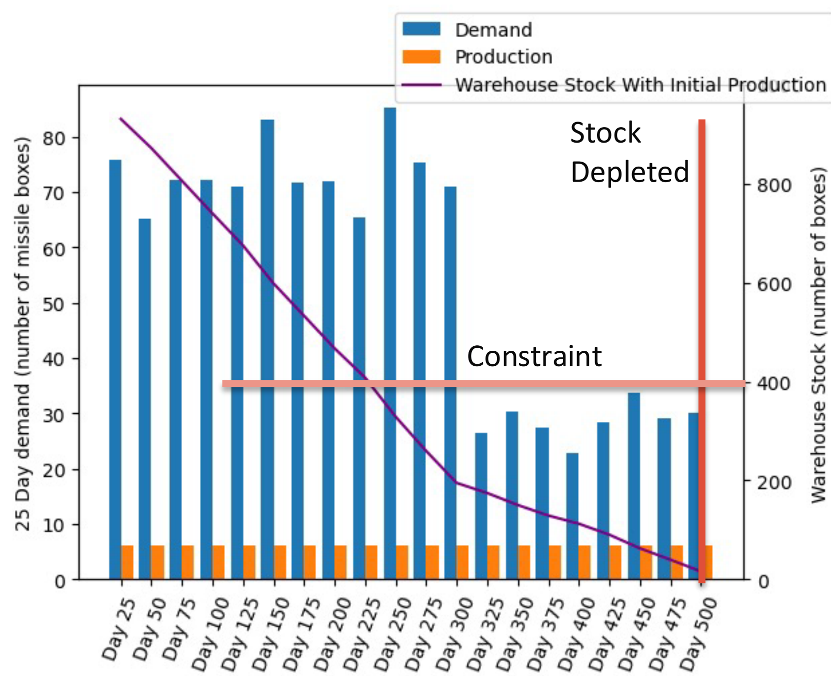

Figure 6. Demand, Production, and Stock Under a Notional Factory Setup

While this setup extends the stockpile to day 500, it fails to meet the requirement of maintaining at least 400 missile boxes in inventory by the end of the mission. To satisfy this constraint, adjustments to the production floor are necessary. The first step is to determine the required throughput, which can be calculated by comparing total inflows and outflows, as shown in Equation 1. In this equation, *P* represents the desired throughput, *sg* is the number of 25-day segments, S_i is the starting stock, S_L is the target ending stock, and D_k denotes the demand. For this scenario, the required throughput is 25.4 missile boxes per 25-day period, equivalent to 101.6 missile boxes per 100 days.

$$P = \frac{S_i - S_L - \sum_{k=1}^{sg} D_k}{-20} \tag{1}$$

The objective is to increase production from 6.2 to 25.4 missile boxes over a 25-day period (equivalent to 101.6 boxes over 100 days). To identify the production steps that most strongly affect throughput, the simulation results were analyzed using JMP's predictor-screening capability. As shown in Figure 7, the most influential steps are filament winding, pod drilling, pod trimming, and heat curing.

	Missile box made Response			Missile pods made Response		
Predictor	Contribution	Portion	Rank	Contribution	Portion	Rank
Filament Winding Number of Machines	915999	0.2612	1	48767684	0.2553	1
Drill machines Number of Machines	761031	0.2170	2	41384490	0.2166	2
Trimming Machines Number of Machines	748562	0.2135	3	40306383	0.2110	3
Mandrel Extraction Number of Machines	681230	0.1943	4	39552679	0.2070	4
Heat cure capacity	194383	0.0554	5	10002908	0.0524	5
Post Heat cure capacity	164301	0.0469	6	9438305.9	0.0494	6
Filament Winding time (min)	5902	0.0017	7	422825.81	0.0022	7
Insertion Pods Structure time (min)	5737	0.0016	8	350097.68	0.0018	8
Control: Arnament Delivery Disruption Amount of Delay (Time)	4460	0.0013	9	6930.6843	0.0000	34

Figure 7. JMP Predictor Screening, Missile Box and Missile Pods Throughput

Using the surrogate model, a profiler was generated to show how missile-box throughput changes in response to modifications on the factory floor. The profiler reports throughput in 100-day intervals; values for a 25-day period can therefore be obtained by dividing by four. As shown in Figure 8, increasing the number of filament winding machines produces a corresponding increase in overall system throughput.

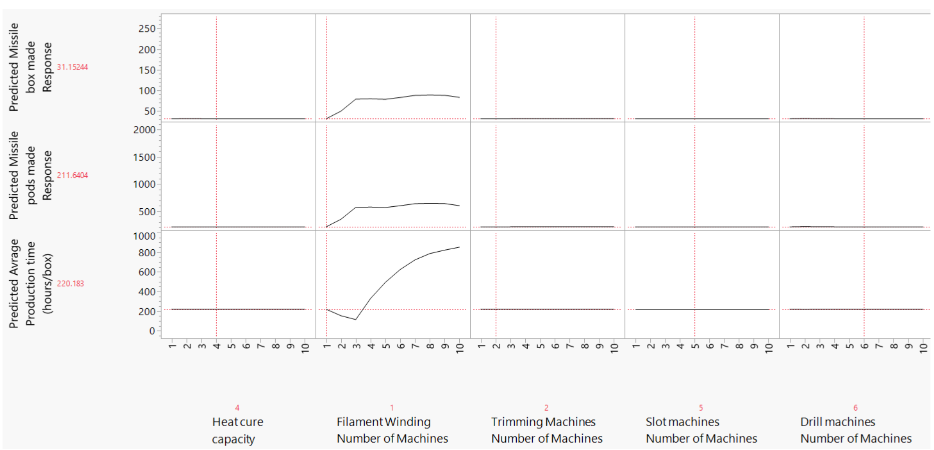

Figure 8. Predictor Profiler With Initial Setup

Increasing the number of filament-winding machines from one to three raises throughput from 31 to 78.8 missile boxes per 100 days. Although this is a substantial improvement, it remains below the required 101.6 boxes per 100 days. No single change is sufficient to close the gap. However, the predictor-screening results in Figure 7 indicate that drilling and trimming are also important contributors to throughput. The updated facility layout therefore adds three filament-winding machines and one trimming machine. As shown in Figure 9, this configuration increases throughput to 103.6 missile boxes per 100 days, or 25.9 boxes per 25 days. That output exceeds the target throughput of 25.4 missile boxes per 25 days. Figure 10 shows the resulting relationship between stock levels and demand under the revised setup.

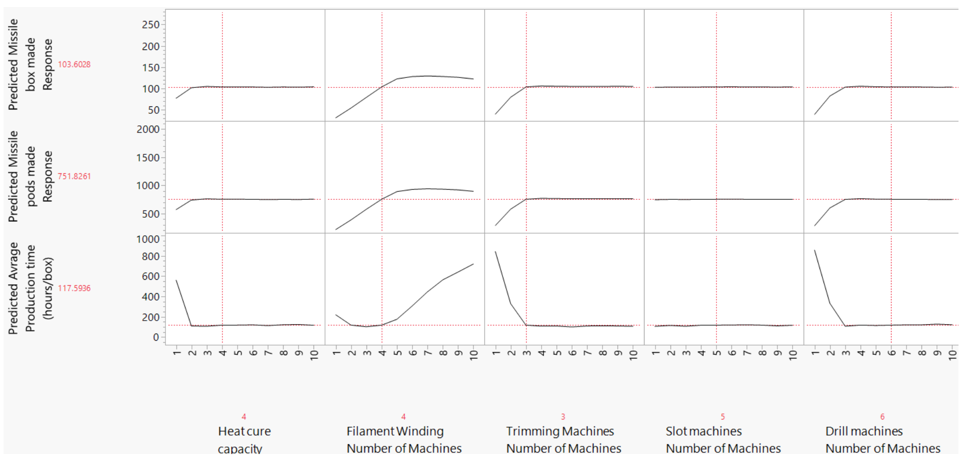

Figure 9. Predictor Profiler With the Number of Filament-Winding Machines Increased by Three and Trimming Machines by One

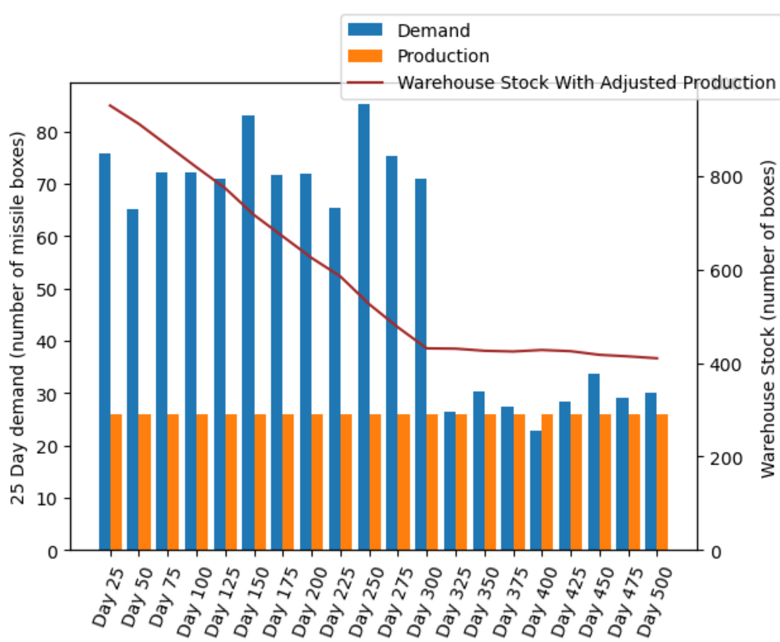

Figure 10. Demand, Production, and Stock Under the Adjusted Factory Setup

Scenario Two

Scenario Two begins where Scenario One ends. After the initial mission concludes, it is determined that an additional surge in missile expenditure is required. This introduces a new 300-day period of high demand. The scenario begins with a remaining stockpile of 410 missile boxes, which is the ending inventory from Scenario One. Unlike the previous case, this surge is not identified until day 500, so production changes cannot be implemented in advance.

In Scenario Two, modifications to the production floor require time to implement. For example, if a set of changes takes 100 days, the higher throughput is not realized until 100 days into the scenario. Each machine change is assumed to require 25 days, and the time required for multiple changes is additive; for instance, two changes require 50 days. In addition, all changes must be completed before the new production capacity becomes active, so staggered implementation is not allowed.

As shown in Figure 11, the factory configuration established in Scenario One is insufficient to meet the new demand, and the stockpile is fully depleted by day 725.

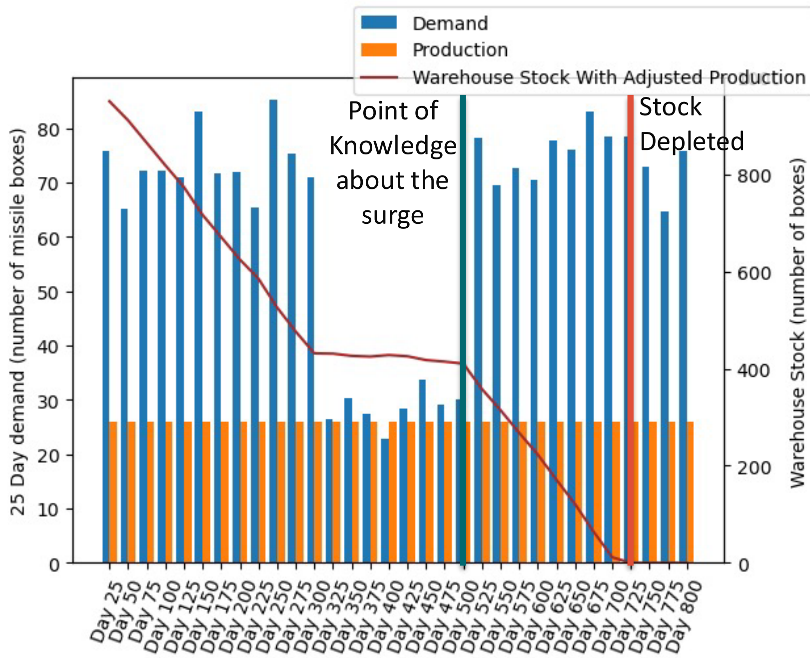

Figure 11. The Extended Scenario With Throughput Given by the Adjusted Manufacturing Facility

Given these constraints, an equation can be formulated that defines the relationship between the number of changes and the required throughput. This relationship is expressed in Equation 2, where *sg* represents the total number of 25-day segments, *c* is the number of 25-day segments at new production rate, P_1 is the initial throughput, and P_2 is the modified throughput.

$$c(P_1 - P_2) < S_i + (sg)P_1 - \sum_{k=1}^{sg} D_k \qquad (2)$$

The result of this relationship is shown in Figure 12. Since each change takes 25 days to implement, adding a single change reduces the time available at the new throughput rate from 12 segments to 11. Initially, the increase in required throughput is approximately linear, between

8 and 12 segments under the new production rate. Beyond this range, however, the required throughput begins to rise much more sharply.

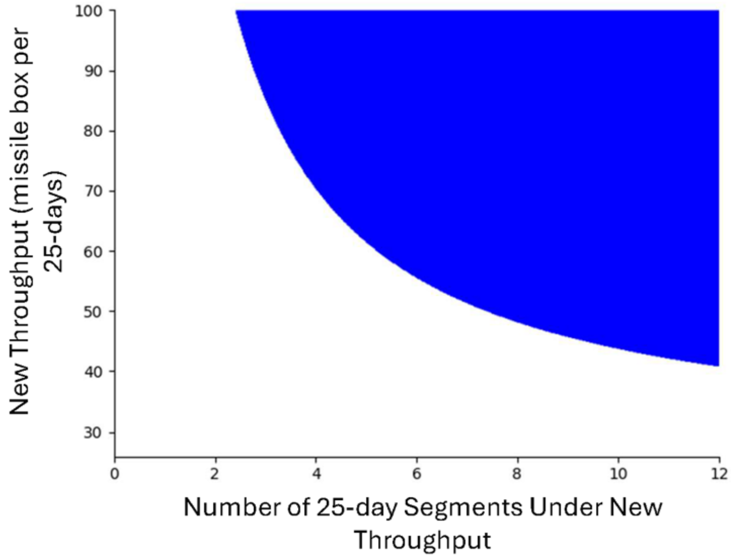

Figure 12. Trade-Off Between the Number of Changes and the Required New Throughput

As the number of changes increases, so does the required throughput. By examining the throughput deficit using Equation 3, it is possible to assess whether the new mission demand can be met.

$$Deficit = \frac{New\ Throughput - Needed\ Througput}{Needed\ Througput} \tag{3}$$

The results, shown in Table 7, indicate that up to four changes reduce the throughput deficit. When the number of changes increases to six, requiring 150 days to implement, the deficit begins to worsen. This occurs because the throughput gains from adding machines are outpaced by the increase in required production. As illustrated in Figure 13, implementing four changes allows the stockpile to last until day 750. Given the constraints of this scenario, reaching day 750 is the best achievable outcome.

Table 7. The Change of Throughput Deficit Based on the Number of Changes

Number of Changes	Throughput Deficit (%)
1	27 %
3	15.6 %
4	13.76 %
6	15.27%

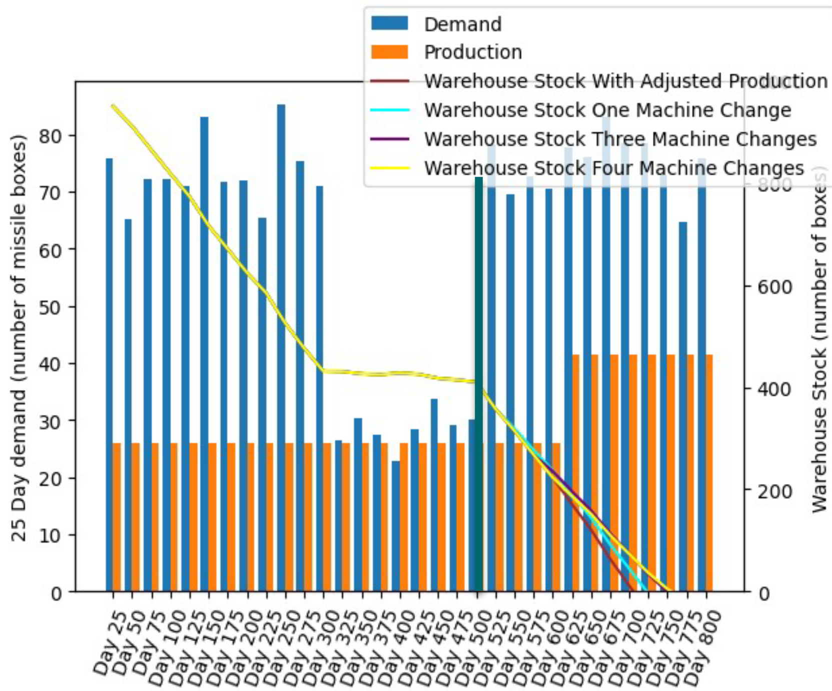

Figure 13. The Extended Scenario With Throughputs With Different Number of Changes

Conclusions and Future Work

A comprehensive parametric modeling and simulation environment was developed to examine how manufacturing capacity affects the ability of the broader factory-to-field system to satisfy operational demand. Using SEER-MFG to estimate manufacturing-process times and SIMIO to quantify throughput for a given factory configuration, the environment provides a rapid and flexible means of evaluating how changes on the factory floor influence production performance. In total, the model includes 65 adjustable inputs, allowing users to examine the effects of assumptions related to quality control, machine quantity and capacity, delivery delays, and inventory-storage limits. In this sense, the contribution of this work is a manufacturing-focused component of a larger decision-support framework intended to connect demand, logistics, and production.

Two operational scenarios were used to demonstrate these capabilities. In the first scenario, all production changes were assumed to be implementable before mission start. The results showed that the environment can identify whether a given factory configuration is sufficient to satisfy mission demand and can rapidly evaluate how changes in production resources affect throughput. In the second scenario, production changes had to be made during mission execution, introducing time-dependent implementation constraints. This case demonstrated the environment's value for assessing the consequences of delayed action and for characterizing the relationship between implementation time and the level of production capacity required to recover. Taken together, these scenarios show that the modeling environment can support timely and structured assessment of manufacturing responsiveness under both preplanned and dynamically evolving conditions.

More broadly, this work addresses a critical need in defense planning: the need to link operational demand to the logistics, manufacturing, and production systems required to sustain combat capability. In contested or time-sensitive environments, it is not enough to understand demand in isolation; planners must also understand whether the industrial base and supporting supply chain can respond at the speed and scale required by the mission. Studies that connect demand forecasting, logistics timelines, manufacturing constraints, and production throughput are therefore essential for evaluating resilience, identifying bottlenecks, and informing resource-allocation decisions across the end-to-end system. The manufacturing and production models presented here contribute to that larger objective by providing a structured way to assess how factory-floor decisions influence the ability to meet scenario-driven demand.

Future work should focus on increasing both the fidelity of the manufacturing representation and the degree of integration across the broader modeling environment. Important extensions include relaxing simplifying assumptions and incorporating additional decision variables such as workforce availability, work-shift structures, material characteristics, part geometries, maintenance constraints, and facility-layout considerations. Future studies should also examine how existing manufacturing facilities and supply chains absorb new or surge demand without degrading support to other high-priority operations. Most importantly, the manufacturing model should be fully integrated with the Phase I logistics model described in the Methodology and associated with Figure 1 to enable a much-needed end-to-end analysis of how operational demand propagates through transportation, inventory, and production systems. Such integration would significantly improve the utility of the framework as a decision-support tool for planning resilient defense industrial operations under uncertainty.

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SEER-MFG is a trademark of Galorath Incorporated.

SIMIO is a trademark of Simio LLC.

MLRS is a trademark of Lockheed Martin Corporation.

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