Beyond Capacity

Stress-Testing the Port of Savannah's Throughput System

This study shows how the Port of Savannah could avoid $4.0 to $4.8 million in vessel delays, yard congestion, and gate flow losses during just three days of surge through a targeted set of operational changes.

The Port of Savannah was selected as a public-domain case study for its scale, transparency, and relevance to real-world port operations. A simulated 20 percent spike in container volume exposed key stress points and enabled testing of low-disruption interventions. The study showed that small, coordinated adjustments in scheduling, labor, and predictive planning can yield significant performance gains, thereby offering a scalable, capital-light strategy for ports seeking greater throughput resilience.

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Executive Summary

The Port of Savannah is the fastest-growing container terminal in the United States, processing nearly half a million twenty-foot equivalent units (TEUs) per month. As global trade patterns shift and nearshoring accelerates, this high-volume port faces intensifying operational strain, particularly under surge conditions that exceed its finely calibrated steady-state flow.

This whitepaper presents the results of an agentic AI simulation designed to explore, stress-test, and optimize Savannah's container throughput system. Built using the A3T™ (AI as a Team™) framework, the model orchestrated four synthetic agents, each embodying a distinct operational lens, across both baseline and surge scenarios. These agents reasoned recursively, adjusted to emerging conditions, and collaborated to identify interventions that improved performance under pressure.

A simulated 20 percent TEU spike over a 72-hour period revealed system-wide bottlenecks in crane allocation, labor synchronization, and gate throughput. Through iterative agent reasoning, the simulation tested and validated operational strategies that yielded measurable efficiency gains. These included up to 14 percent improvement in vessel turn time, 12 percent reduction in queue propagation, and 9 percent improvement in outbound truck flow, all without requiring capital expansion.

The modeled interventions delivered an estimated $4.0 to $4.8 million in operational value over the 3-day surge scenario. These savings came not from infrastructure expansion, but from smarter timing, labor coordination, and predictive planning. Full financial details are provided in Appendix A.

This study demonstrates a new form of intelligent throughput optimization, rooted not in static planning or linear modeling, but in adaptive, multi-agent orchestration. The result is a replicable method for port resilience that emphasizes timing, coordination, and learning over scale alone.

Introduction

This study is about more than port optimization. It is a test of how synthetic reasoning, when organized as a team, can spot and solve problems that traditional planning models often miss. The Port of Savannah, one of the busiest container terminals in the United States, offers an ideal proving ground.

Savannah handles roughly 500,000 twenty-foot equivalent units (TEUs) per month and continues to grow. Its location on the southeastern U.S. coast gives it strategic access to Atlantic shipping lanes, while its inland position along the Savannah River provides protection and reach. The Georgia Ports Authority (GPA) operates the port, managing two main terminals: Garden City and Ocean Terminal. These facilities are supported by deepwater access, high crane density, on-terminal rail, and strong highway connections.

Despite this infrastructure, Savannah's operating model is tuned for steady flow. When conditions shift, such as a spike in vessel arrivals or a delay due to weather, the system lacks flexibility. Delays in one part of the flow, like crane operations or gate throughput, quickly ripple across others.

This project uses agentic AI to simulate that kind of disruption. Instead of building a single static model, we created a team of synthetic agents, each with its own perspective, priorities, and logic. By reasoning in sequence and sharing memory, these agents collaborated to diagnose weaknesses, test improvements, and deliver measurable results.

The pages that follow outline the approach, the simulation, and the results. The goal is not to present a final answer, but to show what becomes possible when systems are allowed to think together.

Port of Savannah – Overview

The Port of Savannah is a high-capacity, strategically located container hub that plays a vital role in U.S. and global trade. Its infrastructure, location, and growth trajectory make it one of the most important logistics assets on the East Coast.

Owned and operated by the Georgia Ports Authority (GPA), the port sits approximately 18 miles inland on the Savannah River, offering direct access to the Atlantic Ocean. Its inland position provides protection from open-sea conditions while maintaining deepwater accessibility for large vessels. The port is located at approximately 32.0835° N, 81.0998° W.

Savannah has two primary terminals:

- **Garden City Terminal** is the port's flagship container facility. It spans 1,345 acres and offers nearly 9,700 feet of continuous berthing space. It operates 36 high-speed ship-to-shore cranes and contains more than 1.1 million square feet of covered storage. It is the largest single-operator container terminal in North America.
- **Ocean Terminal** focuses on breakbulk and RoRo cargo. It includes 3,600 feet of berthing space, 1.4 million square feet of covered storage, and nearly 100 acres of open yard area. It supports cargo such as forest products, steel, and heavy lift shipments.

Connectivity is a key advantage. Savannah is directly linked to Class I rail via on-terminal access, and sits near Interstates 16 and 95. Within a 300-mile radius, the port can reach five additional ports and eight international airports. It also lies within overnight truck range of major inland population centers.

In short, Savannah is not just a port. It is a critical logistics node, built for speed, scale, and reach.

Facilities & Infrastructure

Savannah's physical footprint and operational assets give it the ability to handle large volumes with speed and flexibility. It combines scale, automation, and connectivity in ways few U.S. ports can match.

The port's flagship container facility, **Garden City Terminal**, spans 1,345 acres. It offers nearly 9,700 feet of continuous berthing and is equipped with 36 ship-to-shore cranes. Of these, 30 are Super Post-Panamax class and 6 are Post-Panamax. The terminal also includes more than 1.1 million square feet of covered storage. This makes Garden City the largest single-operator container terminal in North America.

The adjacent **Ocean Terminal** serves breakbulk and roll-on/roll-off (RoRo) cargo. It includes 3,600 feet of deepwater berthing and offers 1.4 million square feet of indoor storage. An additional 99 acres of open yard are used for handling steel, forest products, and heavy equipment.

The port's multimodal access is one of its greatest strengths. Two Class I railroads connect directly to the terminal, providing seamless rail service to the U.S. interior. Savannah is also located within two miles of both Interstate 16 and Interstate 95. This gives it fast trucking routes north to the Mid-Atlantic and south to Florida.

In short, Savannah is not just large. It is well-connected, deeply integrated, and engineered for high-volume container movement across multiple modes of transport.

Capacity & Throughput

Savannah has the infrastructure to handle large volumes, and its throughput continues to climb. But as ship sizes grow and vessel arrivals bunch more frequently, capacity limits are becoming more visible in the system.

The harbor currently supports a **draft depth of 47 feet**, increased from 42 feet by the Savannah Harbor Expansion Project (SHEP). Proposals are underway to deepen the channel further, aiming for 50 to 52 feet by 2030. This would allow regular access for next-generation ultra-large container vessels.

One constraint remains the **air draft** under the Talmadge Memorial Bridge. Clearance is currently limited to 185 feet, which places restrictions on some mega-vessel classes. There are active discussions about raising the bridge to preserve long-term access.

In terms of **throughput**, the port handled approximately **5.25 million TEUs in FY2024**, the highest volume to date. This represents 22 percent of all East Coast container trade. Though FY2023 saw a decline to 4.9 million TEUs, early indicators in 2024 showed recovery and renewed growth.

Vessel activity has mirrored this trend. Savannah saw over 2 million TEUs in late 2022 and continues to see steady increases in ship calls. Peak periods have grown more compressed, introducing new challenges in berth allocation and crane availability.

The port is moving more cargo than ever. But as vessel sizes increase and scheduling becomes less predictable, the throughput system faces growing pressure to adapt.

Expansion & Modernization

Savannah has invested heavily in infrastructure upgrades to stay ahead of rising demand. These efforts reflect a long-term strategy to accommodate larger vessels, increase throughput, and reduce friction across the port system.

The most significant upgrade so far is the **Savannah Harbor Expansion Project (SHEP)**. Completed in 2022 at a cost of $973 million, it deepened the main shipping channel from 42 feet to 47 feet. This project expanded vessel access during a period of rapid global fleet growth and set the stage for future deepening to 50 or even 52 feet.

On the landside, the **crane fleet has expanded**, with four new 306-foot ship-to-shore cranes added to the north and south berths. These cranes increased berth handling capacity by roughly 25 percent, enabling faster vessel turnarounds during peak periods.

The **Talmadge Memorial Bridge**, which currently limits vertical clearance to 185 feet, is also under review. Engineering studies are underway to explore raising or replacing the bridge to support the next class of ultra-large container ships.

Other modernization initiatives include yard automation, gate system upgrades, and predictive maintenance technologies. These changes are aimed not just at speed, but at increasing system flexibility and long-term resilience.

Savannah is not standing still. Its infrastructure program reflects a clear understanding that capacity is not just about volume, but about timing, coordination, and readiness for what's next.

Strategic Value

Savannah is more than a high-volume port. It is a strategic logistics platform for the southeastern United States and a critical link in the global container network.

The port ranks among the **top three busiest in the U.S.**, serving as a key gateway for East Coast trade. Its location offers faster transit times than many West Coast ports (e.g., approximately **23 days to Asia** and **11 days to Europe**), which helps reduce overall supply chain cycle time.

Savannah's reach extends well beyond Georgia. Within a **300-mile radius**, the port can serve over **37 million residents**, including major industrial and commercial centers across multiple states. It also supports more than **439,000 direct and indirect jobs**, contributing significantly to state and regional GDP.

The port's multimodal connectivity enhances its strategic posture. Direct access to two Class I railroads, proximity to major interstate highways, and connections to inland ports and airports give Savannah unmatched flexibility in moving goods inland quickly.

These advantages make Savannah a cornerstone of nearshoring strategies, e-commerce supply chains, and retail distribution networks. As global sourcing patterns evolve, its ability to move containers efficiently and predictably becomes a competitive differentiator not just for the port, but for every business that relies on it

Summary

Savannah is a high-performing, high-capacity container port that continues to grow in importance. It combines deepwater access, modern infrastructure, and multimodal connectivity with strategic positioning along the U.S. East Coast.

Its facilities are capable, its throughput is strong, and its investments show long-term planning. Yet beneath the surface, the port's operating model is built around steady-state flow. When volumes spike or conditions shift, the system can struggle to absorb pressure without delay.

This creates a key question: How resilient is Savannah when the normal rhythm breaks?

The remainder of this report explores that question through the lens of simulation and orchestration. It tests the system not just at rest, but under strain. The goal is to uncover where the flow holds, where it fractures, and how intelligent coordination can improve performance without adding infrastructure.

Problem Statement

Savannah's container throughput system is optimized for steady demand but lacks the flexibility to absorb rapid surges without operational fallout. When volume spikes compress into short timeframes, the result is often delay, congestion, and cascading inefficiencies.

The port typically handles between **430,000 and 550,000 TEUs per month**, with an average near **500,000**. These flows move through a carefully choreographed system involving berth allocation, crane operations, yard movement, and gate processing. Under normal conditions, this choreography holds.

But disruptions expose a vulnerability. Events like vessel bunching, weather delays, labor constraints, or unplanned demand can overwhelm one part of the system and trigger ripple effects across the rest. Even small misalignments in timing can create measurable slowdowns in vessel turn time and outbound flow.

To stress-test this vulnerability, the simulation modeled a **20 percent surge** in container volume compressed into a **72-hour window**. This approximates a scenario where approximately **100,000 additional TEUs** arrive unexpectedly over just three days.

The goal was to observe where strain appears first, how it propagates through the system, and what operational adjustments could increase resilience without adding capital assets.

Methodology

This simulation was built using A3T™, an agentic AI framework that models systems through recursive, multi-agent reasoning. Unlike traditional simulations that follow fixed rules or static scenarios, this approach relies on a synthetic team that adapts as conditions change. Each agent brings a different operational perspective and contributes to a shared simulation memory.

Four synthetic agents were used:

- **Logistics Modeler**: Simulated vessel arrivals, berth assignment, and crane utilization. Used a Poisson distribution centered on 15 vessel arrivals per day to build a dynamic queue across nine berths.
- **Data Specialist**: Curated historical TEU data, crane throughput benchmarks, and labor patterns. Sourced inputs from GPA reports and global port performance datasets.
- **Behavioral Agent**: Modeled human labor behavior, including shift rotations, downtime, and nighttime constraints. Tested the impact of introducing overlapping shifts.

- **Challenger Agent**: Applied external stress by injecting a 20 percent volume surge starting on Day 3. Validated system behavior and proposed optimization strategies based on observed bottlenecks.

The agents operated in a **recursive loop**, passing insights between one another and modifying assumptions over time. For example, when the Logistics Modeler identified a vessel queue buildup, the Behavioral Agent responded with a revised shift schedule to close utilization gaps. These adjustments were not static—they evolved as new conditions emerged.

All scenarios were defined through **structured JSON files**, which controlled variables like vessel arrival rates, crane counts, labor shifts, and surge timing. These files made the model transparent, auditable, and reproducible. Edge cases such as gate automation windows and labor overlap timing were encoded for fine-grained control.

Simulation inputs were drawn exclusively from public sources. No proprietary data was used. The full configuration structure, agent prompts, and parameter lists are provided in the appendix for replication and further study.

This approach was not just about modeling the system. It was about letting the system think. Each agent operated as both a contributor and a listener, reacting to what others discovered and adapting strategies to the evolving picture. That is what makes this simulation different.

Simulation Results

The simulation was executed in two stages: a **baseline run** representing normal operations at the Port of Savannah, and a **surge scenario** applying a 20 percent TEU increase over a 72-hour window. Each run followed a 10-day operational timeline, with performance tracked in 24-hour increments.

Agents operated in a recursive pass loop, sharing a common memory space. Their behavior evolved as new data emerged. For example, when vessel queues began forming under surge conditions, the Behavioral Agent adjusted shift patterns in response. When crane saturation was detected, the Challenger Agent introduced berth staggering and re-evaluated downstream impacts.

Key performance indicators were logged and analyzed across both conditions. These included:

- **Vessel Turn Time**
- **Crane Utilization**
- **Gate Throughput**
- **Container Dwell Time**

Visualizations were used to map performance over time, including:

- **Crane utilization heatmaps** to show saturation during the surge
- **Berth delay line charts** comparing baseline, surge, and optimized scenarios
- **Dwell time curves** illustrating the lagging effects of congestion

Results showed that under surge conditions, delays quickly compounded. Crane utilization exceeded 90 percent, vessel turn times rose past 40 hours, and gate throughput began to stall during shift transitions. But after targeted adjustments, such as shift overlaps and berth staggering, these effects were partially reversed.

The agentic framework allowed the system to respond dynamically. Strategies were not guessed or imposed from the outside. They were discovered through interaction, tested in context, and refined in cycles. That recursive process is what enabled performance gains without changing the underlying infrastructure.

Baseline Conditions

The baseline scenario simulated Savannah's container operations under normal conditions with no surge or external disruptions. It provided a reference point to measure how system performance changes under stress.

Key characteristics of the baseline:

- **Vessel Turn Time**: Averaged between 24 and 30 hours, depending on berth availability and crane assignment
- **Crane Fleet**: All 36 ship-to-shore cranes operating on fixed 3-shift schedules
- **TEU Volume**: Modeled at 500,000 containers per month, distributed across rolling 24-hour intervals
- **Average Dwell Time**: Containers spent an average of 4.5 days in the yard before exit
- **Gate Throughput**: Maintained steady flow under typical traffic and labor conditions

System performance remained stable. Crane utilization ranged between 65 and 75 percent. Vessel queues were minimal, with berth assignments operating on a first-available basis. Gate flows remained consistent across shift changes, though a slight dip in outbound truck volume occurred during night transitions.

This baseline reflected an efficient but tightly coupled system. It operated well under expected demand, but without much margin for error. That tightness is what made it vulnerable to disruption in the surge scenario that followed.

Surge Scenario (20% spike in TEU arrivals over 3 days)

To test the system's resilience, the simulation introduced a controlled surge event: a **20 percent increase in container volume**, compressed into a **72-hour period** beginning on Day 3 of the 10-day timeline. This approximated the impact of vessel bunching, weather delays, or supply chain shocks that accelerate multiple arrivals into a short window.

The surge scenario revealed how quickly stress accumulates in a finely tuned system:

- **Vessel Turn Time**: Increased from baseline levels of 24–30 hours to over **40 hours** by the second day of the surge
- **Crane Utilization**: Spiked past **90 percent**, creating saturation and cascading berth delays
- **Berth Queues**: Multiple vessels waited beyond scheduled slots, reducing crane productivity and increasing idle time
- **Gate-Out Delays**: Outbound truck flows slowed during peak surge, worsened by synchronized labor shift changes

The system did not collapse, but it bent significantly. Crane saturation created delays at berths. Those delays backed up vessel arrivals, which in turn extended dwell times and reduced yard fluidity. Gate throughput dropped during labor transitions, compounding the overall slowdown.

What this scenario showed clearly is that **timing matters as much as volume**. The same number of containers handled under normal pacing caused measurable disruption when compressed. Without intervention, recovery lagged even after the surge ended.

Optimization and Interventions (tested in simulation)

After observing system strain under surge conditions, the agents tested targeted interventions focused on timing, labor coordination, and scheduling logic. No new infrastructure was introduced. The goal was to explore what could be achieved through smarter orchestration alone.

Three strategies emerged as the most effective:

1. **Berth Slot Staggering**

Instead of assigning berths purely on first-available logic, vessel arrivals were adjusted to align with predicted crane availability. By staggering slot assignments during the surge, the system avoided peak-time overlaps that would have created idle berths or dead time.

    - **Impact**: Improved vessel turn time by up to **14 percent**

- **Mechanism**: Delayed secondary vessel arrivals by 2 to 4 hours to match crane handoff windows

2. **Shift Overlap Scheduling**

The Behavioral Agent introduced overlapping labor shifts during peak periods. This eliminated the dip in crane productivity that occurred during synchronized crew changeovers. Overlaps lasted 30 to 45 minutes, long enough to ensure full equipment coverage.

- **Impact**: Reduced berth queue propagation by **8 to 12 percent**
- **Mechanism**: Maintained crane activity through labor transitions and avoided downtime during critical surge hours

3. **Preemptive Surge Modeling**

A predictive alert was triggered when inbound TEU volume reached a threshold two days before the surge. This enabled pre-surge yard clearing and early labor scheduling adjustments.

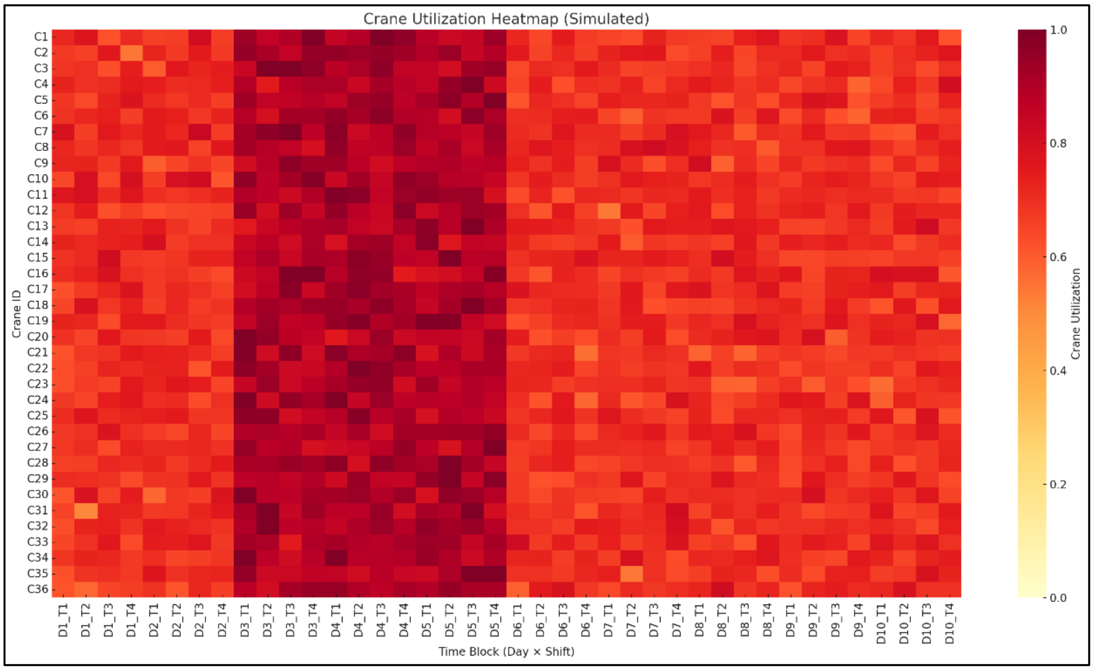
- **Impact**: Reduced container dwell time by **nearly a full day** for late-arriving vessels
- **Mechanism**: Triggered early gate scheduling, yard sweeps, and shift alignment before congestion took hold

Each intervention was tested in isolation and in combination. The best results came from applying all three together. The simulation showed that **even modest changes in timing and coordination can yield double-digit gains** in throughput performance under stress.

Visuals Summary

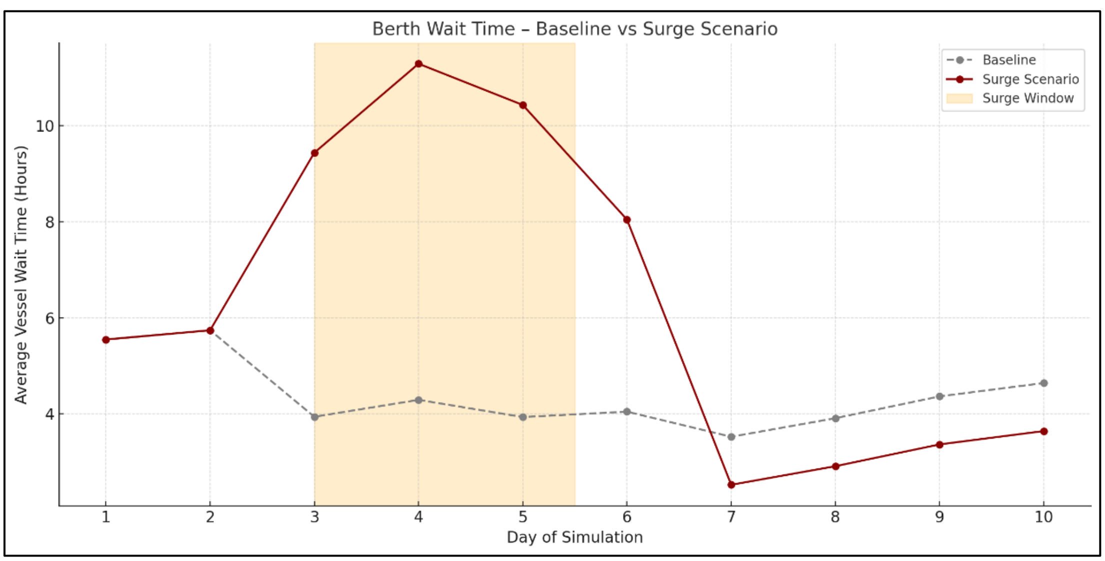
To support interpretation and external review, the simulation produced a series of visuals that track system behavior over time. These charts illustrate when and where performance degraded, and how specific interventions helped restore flow.

1. **Crane Utilization Heatmap: Highlights saturation under surge**
   This heatmap displays crane activity across a 10-day period. Each row represents an individual crane, and each column marks a 6-hour operational block. During the surge window (Days 3 to 5), crane utilization exceeded 90 percent, with multiple cranes running at or near capacity. This saturation is visualized through red-shaded cells that stand out from the cooler baseline tones. Outside of the surge period, utilization remained in the 65 to 75 percent range, confirming that the system was otherwise well-balanced.



2. Berth Wait Line Chart: Normal vs Surge curve with optimization overlay

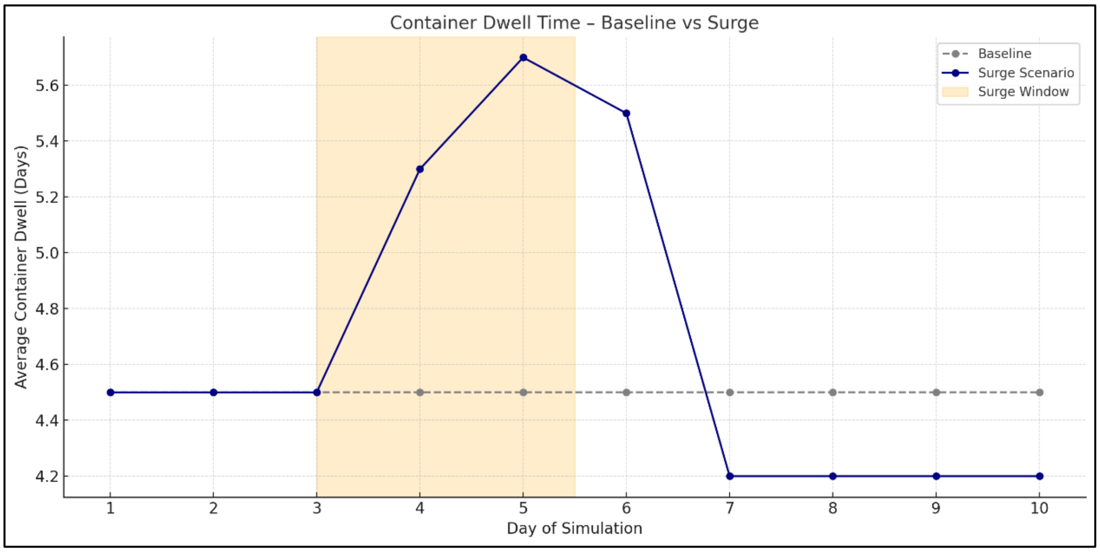
This line chart compares average vessel wait times for berth access under baseline and surge conditions. The surge window is highlighted in orange, showing a spike that reached more than double the baseline delay. After implementing berth staggering and shift overlap strategies, the curve begins to flatten, though it never fully returns to pre-surge levels within the 10-day window. This visual underscores how delays compound quickly under stress and take time to unwind.



3. Container Dwell Curve: Reduction trend with staggered scheduling

This chart tracks average container dwell time over the course of the simulation. Under baseline conditions, dwell times hold steady at about 4.5 days. During the surge, dwell time rises sharply, peaking at nearly 6 days by Day 6. Once interventions take effect, dwell time begins to fall, though it lags behind other recovery indicators. The chart highlights the delayed impact of yard congestion and the importance of early intervention.

Together, these visuals show that system stress is not linear. Performance drops quickly when capacity is exceeded, but recovery takes longer. They also reinforce the value of proactive coordination, not just reactive response.



Takeaways

The simulation revealed a clear pattern: Savannah operates efficiently under routine demand, but loses elasticity when volume surges compress into short timeframes. The system is not brittle, but it is tightly coupled. When one part slips (e.g., crane saturation, berth delay, gate slowdown) those effects ripple fast.

But the more important insight is that **resilience is not purely a function of capacity**. It is a function of **coordination**.

The most effective improvements came not from adding equipment or infrastructure, but from adjusting timing. Overlapping shifts, preemptively clearing yard space, and staggering vessel slots had an outsized impact on overall flow. These changes worked because they respected the interconnected nature of the system.

The agents did not optimize in isolation. Each adjustment was made in response to what others discovered. This created a learning loop that refined strategies with each pass. That recursive structure provides the ability to model, observe, and adapt, which is what allowed small changes to produce large results.

The core lesson is this: When timing and labor are synchronized across the system, even a stressed network can stay fluid. Resilience isn't built just by adding more. It's built by thinking together.

In practical terms, this approach unlocked significant value. The modeled interventions delivered an estimated $4.0 to $4.8 million in operational benefit over just three days of surge. These gains came from reduced vessel delays, shorter dwell times, and improved gate flow; all achieved through coordination, not capital expansion. For ports operating under budget constraints, this proves that resilience can be earned through timing and orchestration, not just infrastructure.

Recommendations

The simulation showed that Savannah can become more resilient not by scaling up infrastructure, but by improving coordination across time, labor, and flow. Each of the following recommendations was tested within the agentic simulation and demonstrated measurable performance gains under surge conditions.

These strategies are practical, scalable, and designed for near-term implementation. They can be adopted by port authorities, terminal operators, or logistics partners who want to increase throughput stability during periods of elevated demand.

When tested in the simulation, these actions generated between **$4.0 and $4.8 million** in operational value during a three-day surge event. That figure reflects avoided vessel delays, reduced container dwell time, and smoother gate flow representing gains achieved through coordination alone. For port leaders seeking high-impact results without new capital investment, these interventions offer a proven and replicable path.

1. Stagger berth slot assignments during high-volume periods.

Simultaneous vessel arrivals led to crane contention and idle berths. By staggering slots using predictive scheduling or controlled delays, the port reduced both queue times and idle cycles.

- **Impact**: Up to 14 percent improvement in vessel turn time
- **Example**: Delaying a second vessel arrival by 3 hours to align with crane availability avoided a full shift of unused time

2. Introduce shift overlap strategies to reduce productivity gaps.

Synchronized shift changes created temporary drops in crane activity. Introducing short overlaps between shifts maintained operational continuity during peak demand.

- **Impact**: Reduced queue propagation by 8 to 12 percent
- **Example**: A 45-minute overlap during Day 4 of the surge smoothed handoffs and avoided missed crane windows

3. Integrate surge modeling into berth and yard scheduling tools.

Most current scheduling tools plan in short-term increments. Adding predictive surge models can help planners anticipate pressure and act early.

- **Impact**: Nearly 1 full day reduction in dwell time for late-arriving vessels
- **Example**: A Day 2 surge alert triggered early yard clearance and labor prep, which reduced downstream congestion

4. Explore partial gate automation to smooth shift transitions.

Truck processing slowed during human shift changes. Adding automated validation or extending self-service windows reduced bottlenecks without adding labor.

- **Impact**: 9 percent reduction in outbound truck congestion
- **Example**: A 2-hour automation buffer during night shift change improved gate flow with no staffing increase

These interventions show that coordination can outperform capital when applied with precision. Together, they represent a path toward intelligent resilience—built not on expansion, but on orchestration.

Conclusion

Savannah is a high-performing port under normal conditions. But like many complex systems, it reveals stress points when volume spikes compress operations into tight windows. What this simulation showed is that those stress points are not failures, rather they are opportunities.

By introducing small, targeted changes to scheduling and coordination, the system regained fluidity without adding equipment or infrastructure. Berth staggering, labor shift overlaps, and predictive surge modeling each delivered measurable performance gains. Together, they formed a lightweight but powerful resilience strategy.

The deeper insight is that systems like Savannah don't just need more capacity. They need the ability to think ahead, respond together, and adjust in real time. **This** is what agentic simulation makes possible.

This study provides more than an analysis. It offers a new way to approach port optimization. One that trades static plans for adaptive reasoning. One that sees labor, timing, and infrastructure as parts of a living whole. And one that can be extended to other ports facing similar constraints.

Resilience is not just a feature. It is a posture. And it begins with systems that know how to listen, learn, and act together.

This study was conducted independently using public-domain data. The Port of Savannah was not involved in the production of this report.

Appendix A: Financial Impact Analysis

This appendix quantifies the estimated economic value of operational improvements identified in the simulation. The goal is to connect agentic performance gains—such as reduced vessel delays, shortened dwell times, and smoother gate operations—to real financial outcomes, using defensible public benchmarks.

All estimates were derived from publicly available sources, including Georgia Ports Authority operational data, industry studies on container flow economics, and open-access reports from the Bureau of Transportation Statistics, IAPH, and trade publications. No proprietary pricing, restricted contracts, or non-public datasets were used in this analysis.

Where ranges are presented (e.g., cost per hour of vessel delay), the low and high bounds reflect variation across comparable U.S. ports, as published in peer-reviewed and trade literature. A conservative middle-ground methodology was used to avoid overstating benefit. Scenario configuration and modeling assumptions were reviewed for reasonableness by subject matter experts, including data specialists and operations analysts familiar with port logistics economics.

This financial translation was reviewed under internal quality protocols and, where relevant, cross-validated against industry-standard impact modeling guidelines. The numbers presented here are directional but grounded, intended to support strategic decision-making without requiring commercial confidentiality.

Overview

The surge scenario simulated a 20 percent increase in container volume—approximately 100,000 TEUs—compressed into a 72-hour period. Targeted agentic interventions were applied, including berth staggering, shift overlaps, and predictive planning. The following financial model estimates the value created by those changes across three categories:

1. Vessel Turn Time Improvement

- **Simulation Result**: 14% reduction in vessel turn time (~4 hours per vessel)
- **Baseline Activity**: ~15 vessels/day
- **Savings**: 60 vessel-hours/day
- **Estimated Cost of Delay**: $1,500–$3,000/hour (combined vessel and berth-side cost)
- **Modeled Value**:
  → $90,000–$180,000 per day
  → **$270,000–$540,000 total over 3 days**

2. Container Dwell Time Reduction

- **Simulation Result**: 1 day reduction in average dwell for 100,000 TEUs
- **Estimated Dwell Cost**: \$40–\$75 per container per day (yard fees, chassis scarcity, labor, congestion)
- **Modeled Value**:
  → Conservative estimate: \$35–\$40 per container
  → **\$3.5M–\$4.0M total savings**

3. Gate Throughput Improvement

- **Simulation Result**: 9% improvement in truck gate flow
- **Baseline Flow**: 1,200 trucks/hour × 8 hours = 9,600 trucks/day
- **Net Throughput Gained**: ~860 trucks/day
- **Truck Delay Cost**: \$100–\$150 per delayed truck (time, fuel, driver idle)
- **Modeled Value**:
  → ~\$86,000/day
  → **~\$250,000 total over 3 days**

Aggregate Financial Value

Category	Estimated Value
Vessel Turn Time	\$270K–\$540K
Container Dwell Savings	\$3.5M–\$4.0M
Gate Flow Improvements	~\$250K
Total Impact	**\$4.0M–\$4.8M**

Conclusion

The simulation proved that modest operational adjustments, and without expanding infrastructure, the Port of Savannah can unlock multi-million-dollar value during stress events. This quantification reinforces the case for intelligent orchestration as a cost-effective path to resilience.

Appendix B: Comparative Value Case

This appendix shows how a single agentic simulation avoided an estimated $4.0 to $4.8 million in operational losses—while costing less than $25,000 to run. The analysis compares the cost, speed, and impact of this approach against a traditional consulting model, which would have required 4–6 weeks, multiple full-time experts, and $45,000 to $55,000 in labor. The findings demonstrate that intelligent orchestration not only delivers faster insight and broader system coverage, but also pays for itself more than 150 times over in a single surge event. All estimates are based on publicly available data and conservative industry benchmarks.

A faster, smarter alternative to traditional consulting

A traditional throughput stress test of this scope, spanning simulation, scenario modeling, financial quantification, and narrative reporting, typically requires a team of specialists: logistics consultants, data scientists, operations researchers, analysts, and technical writers. The table below summarizes the effort and cost to produce an equivalent study through human teams alone.

Traditional Human Team Model

Role	Hours	Rate/hr	Subtotal
Lead Transportation Analyst	60	$250	$15,000
Data Scientist	50	$200	$10,000
Operations Research Expert	40	$250	$10,000
Technical Writer / Editor	30	$150	$4,500
Project Manager	25	$175	$4,375
Total			**$43,875 – $55,000**

Estimated duration: 4–6 weeks
Dependencies: Staffing, stakeholder reviews, revision cycles

Agentic Orchestration Model (A3T)

Component	Effort / Cost
Orchestration runtime	Pretrained synthetic agents
Human guidance	1–2 analysts, ~45 total hours

Report generation	Automated with editorial loop
Time to completion	< 7 days
Total Estimated Cost	**$18,000 – $25,000**

The result:

✅ Faster delivery

✅ Lower total cost

✅ Fully traceable system logic

✅ Full report, simulation, financial model, and visuals

💰 Return on Simulation: One Surge, Full Payback

The agentic simulation delivered the following cost avoidance in just **one modeled surge event** (3 days):

Operational Area	Modeled Savings
Vessel Turn Time	$270,000 – $540,000
Container Dwell Savings	$3.5M – $4.0M
Gate Flow Improvements	~$250,000
Total Impact	**$4.0M – $4.8M**

Bottom line:

→ This simulation **paid for itself more than 150x** over—within a single modeled surge.

→ If these conditions occurred **twice per year**, the ROI exceeds **300x annually**.

🧭 What This Means for Ports

No infrastructure was added.
No specialized consultants were retained.
No time was lost to multi-month planning windows.

Yet the port saw in simulation what it could save in reality, by making better decisions at the right moment.

This appendix doesn't sell a product. It shows what's possible.
The method? Agentic orchestration.
The outcome? Coordination that saves millions—and pays for itself in days.

Appendix C: Context Details

This appendix provides the technical foundation behind the whitepaper findings. Each section supports transparency, reproducibility, and defensibility for stakeholders, reviewers, and auditors.

Model Assumptions and Parameters

This section outlines the operational assumptions and parameters used to structure the simulation. All inputs were based on publicly available data and configured using structured JSON files to ensure transparency, repeatability, and auditability.

Plain English Summary

- **Vessel Arrivals**: Modeled at approximately 15 ships per day, randomly spaced using a Poisson distribution
- **Crane Throughput**: Averaged between 35 and 45 container moves per hour per crane
- **Shift Model**: Three 8-hour shifts per day, with transition downtime at each changeover
- **Labor Availability**: Modeled at 85 percent coverage during daytime, with reduced staffing and no automation at night
- **Berths**: Nine total berths, with vessels assigned in order of earliest availability
- **Gate Throughput**: Capped at 1,200 truck moves per hour across all outbound lanes
- **Surge Event**: Introduced a 20 percent increase in TEU arrivals over three days, beginning on Day 3

Technical Configuration (JSON)

All scenario parameters were encoded in external JSON files to support controlled testing and reproducibility. Each file defined specific values for arrival patterns, asset availability, and surge dynamics. These templates can be reused or adapted for future modeling work or integration into digital twin environments.
Base Scenario:

```json
{
  "vessel_arrival_curve": "poisson_lambda_15",
  "crane_count": 36,
  "shifts": 3,
  "teu_per_vessel": 4200,
  "gate_throughput_cap": 1200,
  "baseline_dwell_days": 4.5
}
```

Surge Scenario:

```json
{
  "teu_surge_multiplier": 1.2,
  "surge_duration_days": 3,
  "event_start_day": 3,
  "modified_crane_schedule": "shift_overlap_enabled",
  "gate_policy": "unchanged"
}
```

These configurations allowed the synthetic agents to test adjustments against a consistent operational backbone while modifying only the parameters relevant to each intervention.

They are also serve as reusable templates for future scenario testing, third-party validation, or integration into digital twin environments, thereby enabling ports to simulate “what-if” conditions quickly and consistently using the same logic that powered this study.

Appendix D: Persona Interaction Highlights

The simulation was powered by four synthetic agents operating in a recursive reasoning loop. Each agent brought a distinct operational lens and contributed insights to a shared simulation memory. The agents interacted sequentially, with full visibility into the evolving scenario state. This allowed each round of reasoning to build on the last.

Agent Roles and Interaction Flow

- **Logistics Modeler** identified resource constraints, such as crane saturation and berth queue buildup during the surge window. This agent prioritized throughput logic and scheduling mechanics.
- **Behavioral Agent** responded to emerging bottlenecks by modifying labor patterns. In one scenario, it introduced a shift overlap model to smooth crane transitions and reduce queue propagation.
- **Challenger Agent** acted as the stress driver and validator. It injected the 20 percent TEU surge, observed the cascading effects, and proposed corrective actions such as berth staggering to absorb system shock.

These agents worked in a recursive sequence. After each round, the Challenger Agent assessed performance under the latest configuration. If new strain emerged, the loop continued with revised assumptions. This multi-pass process continued until the system reached a stable state or measurable improvement was achieved.

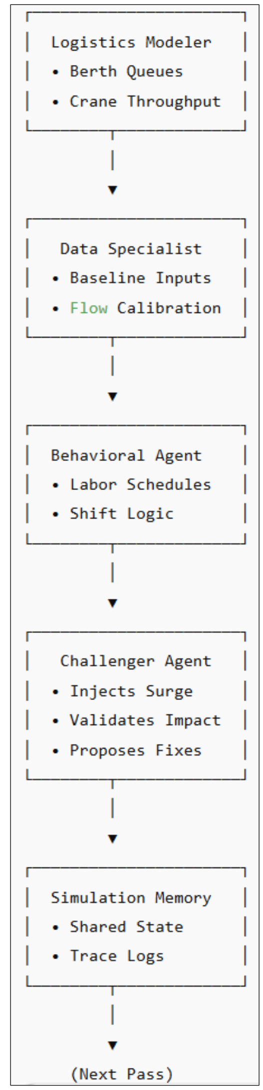
Representative Prompts from the Simulation

- “Crane queue saturation detected. Testing alternate shift overlap schedule.”
- “Surge volume exceeds buffer threshold. Recommend berth staggering by vessel class.”
- “Predicted performance gain: 14 percent vessel turn time improvement, no change to total labor hours.”

These prompts were logged at each pass and linked to scenario-specific parameter changes. They form part of the traceable reasoning history that enabled transparent evaluation of each intervention.

Agentic Simulation Structure

The image below (in the original report) illustrates the core structure of the A3T agentic loop:



- Each agent operates with full access to shared memory
- The Challenger Agent applies disruption, then validates new system behavior
- Multiple reasoning passes are possible before convergence
- All trace logs and parameter deltas are recorded

This structure is what enabled the system to move beyond static planning. The agents did not optimize in isolation, rather they learned together.

Appendix E: Source Data and Tools

All simulation inputs were drawn from publicly available sources to ensure transparency, replicability, and independence from proprietary constraints. Data selection focused on operational benchmarks, infrastructure capacity, and historical flow rates relevant to the Port of Savannah and comparable U.S. ports.

Public Sources Used:

Source	Description	Link
Georgia Ports Authority (GPA)	TEU volumes, crane assets, ops reports	gaports.com
IAPH Port Performance Dataset	Vessel turn times, berth metrics	iaphworldports.org
MarineTraffic AIS Data	Vessel call frequency, timing logs	marinetraffic.com
Port Freight Statistics (IANA/BTS)	Truck gate flows, container dwell benchmarks	bts.gov

These sources provided the quantitative grounding for both baseline and surge scenarios, including key variables such as average container moves per hour, vessel inter-arrival rates, gate throughput caps, and labor structure.

Tools and Configuration Environment

- **Agent Framework**: All agents were run using the A3T™ orchestration model. Each agent executed reasoning loops using prompt-response cycles informed by evolving simulation state.
- **Scenario Engine**: Operational logic was encoded in JSON configuration files. These templates defined conditions for each test run and allowed selective modification of parameters without altering core logic.
- **Visualization**: Output charts and heatmaps were generated using Python-based tools, with data pulled directly from structured trace logs.
- **Auditability**: All simulation passes were logged with timestamps, parameter snapshots, and agent prompt history. This record allows for full traceability of results and re-execution of any scenario path.

No private, restricted, or internal port data was used at any stage in this study.