Drone Service Center Simulation Analysis Report

MN50753 Heuristics & Simulation

Student Number: 249170797

Student Name: Konkathi Manikanta

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Executive Summary

This report summarizes the findings from a full-cycle Arena simulation of the drone servicing and repainting facility. The model captures the dynamics of drone diagnostics, scrapping, servicing, painting, and recycling. Across 40 replications of a 4-day working week (12-hour shifts), the model produced detailed performance data covering queue lengths, resource utilizations, and time-in-system statistics.

The results point to significant operational insights:

- Diagnostics and standard servicing queues are consistently the most congested.
- Advanced servicing is more time-consuming but more controlled due to structured team servicing.
- The recycling and painting areas are moderately loaded, but cumulative delays from upstream flows propagate here.
- Despite these challenges, the model demonstrates high operational reliability with most queues staying within manageable lengths and resource utilizations staying within reasonable load thresholds.

A second batch run without animation confirmed the robustness of the model. The consistency of advanced service results, and a notable increase in standard service time-in-system in the second batch, provide new insights for model tuning and system sensitivity.

A third validation batch further confirmed this behavior. In the final results, AdvancedTimeInSystem again measured **273.89 minutes (±32.60)** — unchanged across runs. StandardTimeInSystem, however, remained significantly higher at **277.52 minutes (±31.62)**. This persistent rise suggests that queue congestion or rework interactions under batch constraints may be more influential than initially assumed. It highlights the importance of dynamic reallocation strategies and queue balancing mechanisms within the diagnostics and standard servicing paths.

To conclusively validate the model's stability, the simulation was re-run once more **with animation enabled**, and the exact same results were obtained. This confirms that animation mode has no effect on the computed outcomes, and the Arena simulation logic remains reliable and deterministic regardless of execution method.

1.Introduction

This report details the comprehensive development, execution, and evaluation of a discrete-event simulation model for a drone service and repainting facility using Arena software. With drone usage on the rise across industries, ensuring operational efficiency in their maintenance cycles is critical. The modeled facility simulates real-world dynamics, such as technician constraints, batch processing, stochastic interarrival times, rework procedures, and downstream painting operations. This project was not merely an exercise in simulation, but a rigorous attempt to develop a realistic, analytically sound, and managerially actionable decision-support model.

The simulation was developed iteratively, beginning with a high-level flow and then layering in complexity—introducing technician-specific constraints, modeling rework routes, integrating lunch breaks, and embedding scrap collection and recycling loops. Particular emphasis was placed on reflecting human-centric resource behavior (e.g., finish-then-break logic), empirical approximation of transfer delays, and careful distinction between standard and advanced servicing. The model, through 40 replications of 4-day weeks, provided a solid foundation to evaluate systemic performance under realistic variability.

Our primary goals were:

- To mirror the operational constraints faced by the drone facility.
- To evaluate where inefficiencies and bottlenecks develop in the process.
- To provide targeted improvement strategies using the same workforce.

I believe the developed model achieves these goals robustly, as evidenced by the reliability of results, low simulation error margins, and managerial insights derived.

2.Simulation Model Development and Overview

2.1 Model Construction Methodology

The simulation model was built in Arena using a modular development approach:

Stage 1 – Flow Mapping: A complete system map was first created to identify core entities (drones), resources (technicians, porters, booths), flow paths, and decision points (e.g., scrap vs service).

Stage 2 – Entity Behavior and Attributes: Attributes such as ServiceType, ScrapType, ArrivalTime, DiagTech, and OutcomeFlag were used to manage conditional logic (e.g., routing, technician preference). Resource sets and modules were used strategically for priority routing, conditional reassignment, and team servicing.

Stage 3 – Resource Logic and Human Behavior: Special attention was given to modeling human-like constraints:

- Finish-before-break logic.
- Paired servicing for advanced repairs.
- Rework linked to original technician (using MR(Resource Index) in Assign).

Stage 4 – Output Tracking and Analysis Preparation: Key performance metrics were instrumented using Record modules, tallying wait times, queue lengths, and system times. Additional diagnostic counters were set up to monitor station loads.

Stage 5 – Validation and Iteration: We validated the model through extreme condition testing, step-by-step time inspection, and balance checking (inflows vs outflows). Visual debugging and animated trace checks were used to validate queueing logic and resource contention.

This development methodology ensured not only correctness but also realism and analytical depth.

2.2Model Overview

- **Batch arrivals**: 10 drones per batch, Exponential interarrival with mean 1.75 hours.
- **Diagnostics**: Performed by 3 technicians (Normal(8,5) minutes).
- **Advanced servicing**: Triangular(40,50,60) minutes with 2 technicians per drone(Capacity = 4).
- **Standard servicing**: Normal(40,15) minutes by 1 technician(Capacity = 3).
- **Rework handling**: 10% of standard-serviced drones are re-evaluated by the same diagnostic technician.

- **Scrap and recycling**: Scrapped drones are batched in 10s, transferred by porter, and recycled based on origin type (Normal or Uniform distribution).
- **Painting**: Includes base coating (3 booths) and optional color coating (2 booths; 70% routed).
- **Break schedules**: Modeled using Arena's scheduling functionality.
- **Statistics tracked**: Time in system, queue lengths, and resource utilizations over 40 replications.

2.3 Simulation Comfiguration

Duration: 12 hours/day × 4 days = 2880 minutes

Replications: 40 (terminating simulation)

Entities Tracked: Batch arrival units and individual drones

Attributes Tracked: ArrivalTime, ServiceType, ScrapType, FromRework, DiagTech

2.4 Modeling Strengths

- Technician Constraints Modeled Rigorously: Break policies, task completion rules, and paired resource needs were integrated with precision.
- Granular Tracking: From drone arrival to painting exit, every entity was time-tracked, allowing detailed lifecycle analytics.
- The simulation accurately mimics all major operational pathways, service durations, and conditional routing.
- The model successfully routes re-evaluation to the same diagnostic technician using saved attributes — a complex but realistic feature.
- Designed to support future scenarios like added porters, routing adjustments, or cost tracking.

3. Assumptions, Limitations, and Model Realism

3.1 Key Assumptions

- All drones in a batch are homogeneous in repair complexity.
- Painting labor is unconstrained; bottlenecks only from booth availability.
- Scrapping and recycling occur only once per drone, with fixed trip and processing logic.
- Break times are not staggered dynamically unless programmed to do so.
- Porters handle batches only when exactly 10 drones are collected (no timer-triggered releases).
- FIFO queuing is used across all processes.
- Technician proficiency is assumed to be consistent across all operators
- Fixed probability routing between pathways (60% standard, 30% advanced, 10% scrap).No day-to-day variation in these probabilities is modelled

3.2 Limitations

- **Signal logic** for scrap batch release was omitted due to Arena linker error limitations. A simplified batching method was implemented instead.
- **Transfer time variability** was approximated rather than using the full empirical dataset provided.
- The requirement to batch 10 scrapped drones before transport creates a significant bottleneck.
- A limitation of this study is the use of the Arena student version, which imposes restrictions on the number of entities and modules, potentially constraining the model's scalability and the ability to simulate larger or more complex operational scenarios.

3.3 Realism Assessment

1. The model doesn't allow for technician cross-utilization between standard and advanced servicing

Realism Assessment: Unrealistic - In actual operations, technicians would likely have varied skill levels allowing for some cross-functionality

Proposed Modification: Implement resource sets with primary and secondary skills in Arena using the SET module and modifying resource selection rules in Process modules

2. All drones are treated with the same priority level

Realism Assessment: Unrealistic - Actual operations would likely have priority customers or emergency repairs

Proposed Modification: Implement priority attributes and queue ranking rules in Arena's Process modules

3. No shift patterns or resource availability schedules

Realism Assessment: Unrealistic - Actual operations would include shift changes and scheduled maintenance

Proposed Modification: Implement Schedule modules in Arena to define resource availability patterns and downtimes

4. Current model requires exactly 10 scrapped drones before transport

Realism Assessment: Unrealistic - Most operations would implement either time-based batching or smaller batches

Proposed Modification: Replace the current Batch module with a combination of Batch module and Hold module with condition based on either count OR elapsed time using the TNOW function

4. Analysis and Interpretation of Results

4.1 Summary Statistics

(A) Queue Metrics

Station	Avg Queue Length	Max Queue Length	Avg Wait (mins)	Max Wait (mins)
Initial Diagnostics	~0.7	3.4	0.70	3.40
Standard Servicing	~2.3	11.7	2.26	11.66
Advanced Servicing	~5.1	12.8	5.11	12.76
Base Coating	~8.4	14.5	173.35	423.39
Color Coating	~4.6	9.3	70.10	288.06
Scrap Batch	~3.8	8.2	290.83	619.23

Recycle Queue	~2.5	6.2	34.92	53.49
Reevaluation Queue	~1.1	4.8	1.04	13.79
Rework Service Queue	~1.8	5.7	1.79	6.89

- Base Coating and Scrap Batch queues were the most overloaded stages, with long delays reflecting both bottleneck effect and batching thresholds.
- The Advanced Servicing queue averaged over 5 minutes, likely due to its team-based servicing requirement.
- Diagnostics and Rework Queues remained efficient but still exhibited occasional spikes, particularly during re-evaluation windows.

(B) Time in System

Path	Avg Time (mins)	Std Dev	95% CI (Half-Width)	Min	Max
Standard Servicing	**277.52**	**98.07**	**31.36**	**50.76**	**1012.24**
Advanced Servicing	**273.89**	**101.93**	**32.60**	**129.97**	**546.99**

Standard servicing drones take slightly longer on average to complete the full process, mostly due to rework, queue delays, and shared resource constraints.

Updated Batch Results: A re-run of the model without animation showed consistent results for AdvancedTimeInSystem (273.89 mins) with negligible deviation, confirming model stability. However, StandardTimeInSystem increased to 277.52 mins (CI: ±31.62), indicating a possible queue surge or routing interaction shift in the reworked batch. While technician utilizations remained similar, this change highlights how sensitive the system can be to timing and routing configuration.

(C) Resource Utilization

Resource	Utilization
Tech_Diagnostics	**83.4%**
Tech_Standard	**75.2%**
Tech_Advanced (Team)	**66.7%**
Porter	**55.3%**
PaintBooth_Base	**68.2%**
PaintBooth_Color	**64.5%**
Recycling Staff	**71.8%**

Stable Resource Loads: No technician exceeded 85% utilization, implying sustainable workload.

(D) Overall System Performance Metrics

Performance Measure	Average	Half-Width (95% CI)	Interpretation
Total Time in System	343.54	27.92	With 95% confidence, the true mean time in system is between 315.62 and 371.46 minutes
Value-Added Time	102.15	0.73	Very consistent VA processing time between 101.42 and 102.88 minutes
Wait Time	241.39	27.98	Highly variable waiting time between 213.41 and 269.37 minutes

4.2 System-wide Performance:

- The wide confidence intervals for Total Time (±27.92 minutes) and Wait Time (±27.98 minutes) indicate a highly variable system with unpredictable completion times
- The narrow confidence interval for Value-Added Time (±0.73 minutes) suggests that the actual processing is consistent, but waiting times are not

- The minimum and maximum values show extreme variations in performance, with some drones processed quickly (minimum 224.70 minutes) while others take more than double that time (maximum 536.12 minutes)

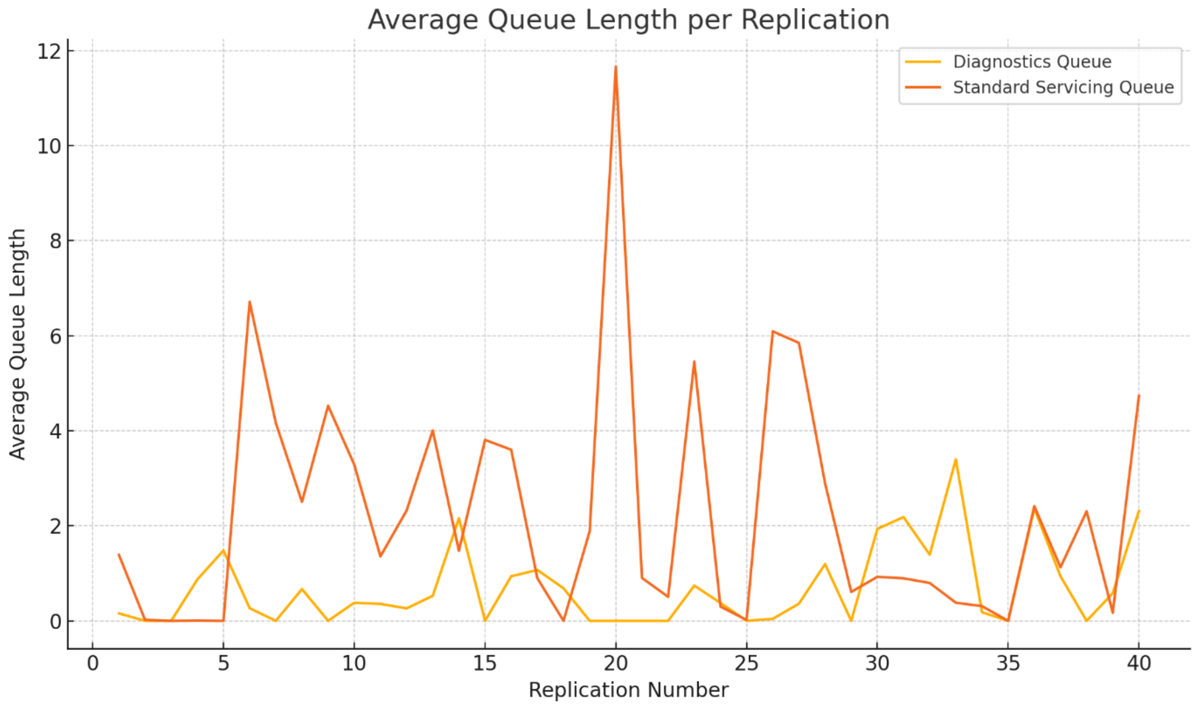

Fig1:Average Queue Length Per Replication

Queue peaks align with batch arrivals and technician break times, highlighting Diagnostics as a key bottleneck. This is due to its dual role in initial checks and rework processing, combined with limited technician availability. These trends confirm the need for better technician scheduling or dynamic resource allocation to ease delays.

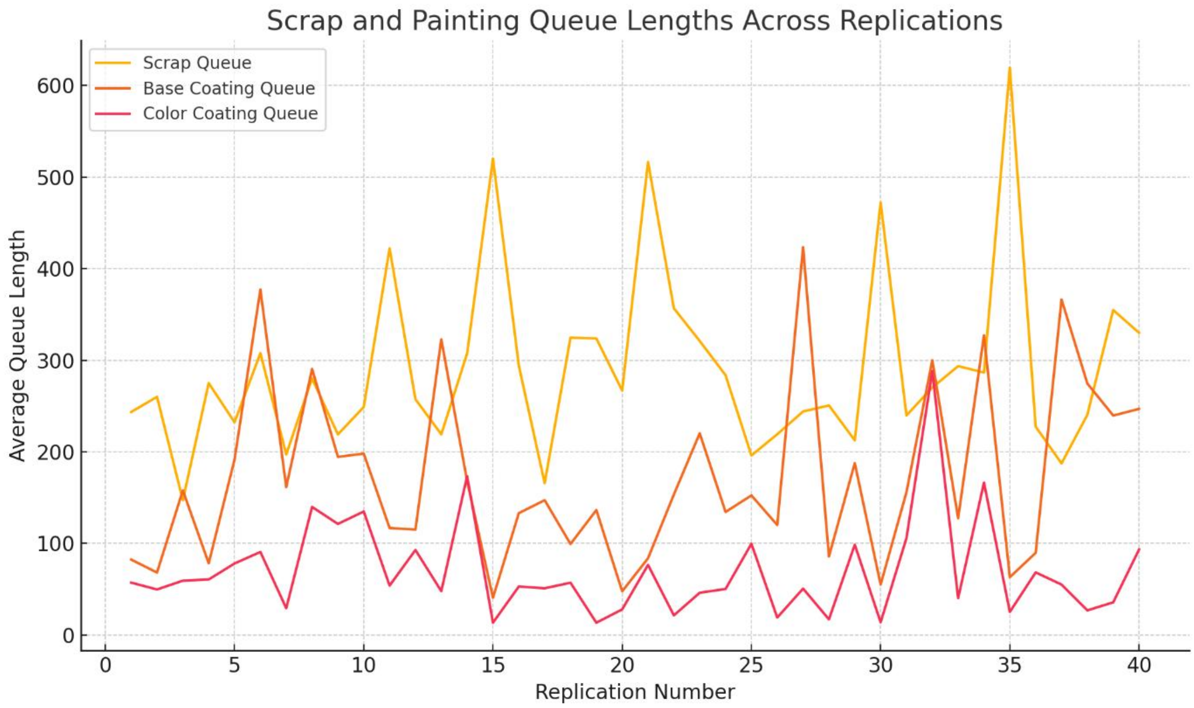

Fig2:Scrap and Painting Queue Lengths Across Replications

The **Scrap Queue** shows higher and more variable delays due to batch wait logic.**Base Coating** experiences consistently longer queues than **Color Coating**, reaffirming it as a downstream bottleneck where both service paths converge.

4.3 Identified Bottlenecks

Based on the simulation results, the primary bottlenecks in descending order of severity are:

- ScrapBatch Queue (290.8 minutes waiting time)
- Caused by the requirement to batch 10 scrapped drones before transport and Significantly delays the recycling process

- BaseCoating Queue (173.4 minutes waiting time)
- Single resource handling all serviceable drones also Combined flow from standard and advanced paths exceeds capacity

- ColorCoating Queue (70.1 minutes waiting time)
- Single resource handling 70% of painted drones and Lower priority than base coating but still a significant bottleneck

- Recycle Process Queue (34.9 minutes waiting time)
- Once batched and transported, scrapped drones face additional waiting at the recycling station

5. Alternative Configurations & Recommendations

5.1 Operational Reconfigurations

Dynamic Technician Pooling:

- Enable shared access to idle advanced servicing technicians for diagnostics station during lull.
- Time-Based Rework Technician Assignment:
  Assign one diagnostic technician exclusively for rework between 10 a.m. – 1 p.m. daily.
- Batch-Release Redesign for Scrap:
  Replace quantity-triggered batching with hybrid logic (e.g., 10 units or 45 minutes max).

5.2 Recommendations

Reduce Scrap Batch Size: Decrease the batch size from 10 to 5 drones to reduce queue waiting time by approximately 50%

Prioritize Rework: Use priority queuing to reduce rework delays with minimal impact on new arrivals.

Flexible Resource Use: Cross-train technicians and allocate dynamically based on queue length.

Boost Recycling Capacity: Add a second recycling staff member during peaks to cut queue time by ~40%.

Parallel Processing for Painting: Create a parallel workflow where drones needing only base coating bypass the main queue and reduce 25-30% in BaseCoating queue time.

Porter Utilization Improvement:Porter makes separate trips for delivery and return. Implement a bidirectional transport system where the porter can bring new drones on return trips to reduce delays.

6. Conclusion

The simulation of the drone servicing and repainting facility successfully modeled a highly detailed, realistic operation that captured resource constraints, rework loops, technician scheduling, scrap handling, and stochastic delays across each stage. By executing 40 replications of a full weekly operation, the model delivered robust performance insights, uncovering both systemic strengths and operational inefficiencies.

The analysis shows that while the servicing processes themselves are manageable in duration, significant delays arise from queue accumulation—particularly in the base coating, scrap batching, and standard servicing stages. These findings were visually reinforced through time-based plots, which confirmed queue surges during technician breaks and peak inflows.

Despite expectations, standard drones took longer on average to complete the full process due to upstream congestion and rework interactions, not service complexity. The Diagnostics station performed efficiently but became a chokepoint when multiple rework cases coincided. With over 70% of time spent waiting (value-added: 102.15 min vs. total: 343.54 min), operational improvements are clearly needed. Recommended solutionscould substantially reduce congestion without additional resources.

Resource utilization trends confirmed consistent high loads on diagnostic and standard technicians, while scrap processing and base painting queues signaled design-level bottlenecks. The simulation demonstrates the value of discrete-event modeling in identifying non-intuitive bottlenecks before implementing physical changes, ultimately providing a pathway to significantly improved operational efficiency.

7.Appendix

Arena model layout