Technical Report Summary: Delta Sky Broadcasting Operations Analysis

# Section 1: Introduction

This report analyses Delta Sky Broadcasting's field operations for new satellite TV installations, focusing on five key operational components. The study examines eight weeks of call-centre data, identifying patterns through cantered moving averages and extracting median daily profiles. The analysis then compares three forecasting methodologies—seasonal naïve, seasonal average, and seasonal exponential smoothing, using multiple error metrics across both in-sample (May 1–June 18) and out-of-sample (June 19–25) periods.

For inventory management, the report simulates a seven-day (s,Q) policy for satellite boxes with a reorder point of 2 and order quantity of 10, calculating holding, ordering, and backorder costs through Monte Carlo simulation. It also optimizes engineer deployment through linear programming, minimizing travel distances across five technicians and five installation jobs. Additionally, the research models Saturday vehicle servicing operations using an M/M/2 queuing system to evaluate mechanic utilization and vehicle wait times. Based on comprehensive analysis across these operational domains, the report recommends implementing seasonal exponential smoothing for demand forecasting, optimizing safety stock through forecast-driven reorder points, employing algorithmic job assignments for technicians, and implementing dynamic staffing for service bays. These integrated improvements will reduce operational costs while maintaining timely installation service as subscription volumes grow.

# Section 2: Investigating New Subscription Call Demand

Daily call volumes for new subscriptions between 1 May and 25 June 2023 were decomposed to reveal their systematic structure. All analyses use an additive classical model Xt = Tt + St + et, appropriate because the amplitude of the seasonal swings is effectively constant across the June level change.

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Figure 1:  Daily call series with 7-day CMA (Source: Author)

Figure 1 overlays the raw series with a 7‑day centred moving‑average (CMA). A seven‑day window was chosen because the initial plot suggested a weekly rhythm; averaging one complete Monday‑to‑Sunday block removes that rhythm and exposes the underlying level (Box, et al., 2015). The CMA shows a stable plateau in May (≈1 600 calls day⁻¹), then a sharp uplift of ~650 calls commencing 4 June, followed by a slight taper after 18 June, evidence that the early‑June marketing push had an immediate yet short‑lived impact.

Table 1: Detrended residual matrix (Week × Weekday).(Source: Author)

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Seasonal isolation.  
Subtracting the CMA from each observation produced the detrended residuals, these were arranged in an eight‑by‑seven seasonal matrix (Table 1). Column medians gave the weekday seasonal component Sk, plotted in Figure 2. The profile is highly asymmetric: Wednesday is the peak (+402 calls), Monday, Tuesday and Thursday are modestly above trend, Friday is neutral (–144), and weekend days plunge to –624 (Saturday) and –578 (Sunday). Low intra‑column variance (CV < 0.35) confirms the weekly pattern is stable, justifying the additive assumption.

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Figure 2: Median weekday seasonal profile (Source: Author)

## Implications for planning.

* Call‑centre staffing: The 1,000‑call swing between Wednesday and Saturday equates to roughly 33 agent‑hours per hub. Rostering can therefore be re‑balanced adding 20–25 % heads Monday‑Thursday and trimming weekend shifts without worsening service levels.
* Field‑engineer deployment: Installations lag calls by ≤24 h, so hubs should stock additional satellite boxes and schedule extra engineers Tuesday‑Thursday, reducing Saturday idle inventory.
* Marketing scheduling: Campaigns launched on Friday will push incremental volume into the natural weekend trough, smoothing utilisation; Monday launches risk overloading the mid‑week peak.
* Forecast design: Any reliable short‑term forecast must include a weekly seasonal component and allow for discrete level shifts; models that neglect these features will systematically under‑ or over‑predict (Hyndman & Athanasopoulos, 2021).

In summary, the eight‑week data exhibit a pronounced, repeatable weekday cycle super‑imposed on a June level shift. Quantifying both components provides the statistical foundation for the forecasting, inventory and resource‑allocation analysis that follow.

# Section 3: Forecasting New Subscription Call Demand

Using daily call data from 1 May to 18 June 2023 as in‑sample, applied three seasonal methods—seasonal naïve (SN), seasonal average (SA), and seasonal exponential smoothing (SES), to generate one‑step‑ahead in‑sample forecasts and a fixed‑origin seven‑day forecast (19–25 June). Model parameters were chosen by method default: SN uses a 7‑day lag, SA computes the expanding average of each weekday, and SES employs Excel’s FORECAST.ETS (seasonality = 7 days, automatic smoothing parameter).

**In‑Sample Performance (1 May–18 June)**

* **SN**: ME = +87.19, MAE = 508.35, RMSE = 661.57
* **SA**: ME = +160.80, MAE = 518.87, RMSE = 654.72
* **SES**: ME = –22.90, MAE = 440.60, RMSE = 510.25

SES outperforms both SN and SA on MAE (440.60 vs. ~513) and RMSE (510 vs. ~658), indicating superior bias correction and reduced large errors. Its slightly negative ME (–22.90) suggests a marginal under‑prediction, whereas SN and SA both exhibit positive bias.

**Out‑of‑Sample Performance (19–25 June)**

* **SN**: ME = +35.14, MAE = 543.14, RMSE = 708.40
* **SA**: ME ≈ –2.43, MAE = 497.57, RMSE = 741.35
* **SES**: ME = +1 067.18, MAE = 1 096.78, RMSE = 1 446.51

Here, SA’s near‑zero ME and lowest MAE (497.6) indicate the best out‑of‑sample accuracy, despite moderate RMSE. SN remains moderately biased positively and shows larger variability. SES severely over‑forecasts (ME > 1 000), likely due to parameter over‑fitting to in‑sample seasonality, failing to capture the abrupt mid‑June spike.

**Metric Considerations**  
MAE provides a clear measure of average absolute deviations, insensitive to error sign and outliers; RMSE penalizes large errors more heavily, while ME indicates directional bias. SES’s strong in‑sample but poor out‑of‑sample performance underscores the risk of optimizing solely on in‑sample RMSE without validating forecast stability (Makridakis, et al., 1998).

**Model Choice**

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Figure 3: Actual vs. SN, SA, SES forecasts (10–25 Jun).(Source: Author)

The chart plots actual call volumes (blue) against the three seven‑day ahead forecasts for 10–25 June. All methods capture the sharp mid‑June trough and late‑June rebound, but with varying fidelity:

* **Seasonal Naïve (orange)** typically overshoots the trough and under‑reacts to the rebound, reflecting its rigid one‑week‑lag structure.
* **Seasonal Average (gray)** smooths extreme swings, producing gentler peaks and troughs—good for reducing noise but slow to track sudden shifts.
* **Seasonal Exponential Smoothing (yellow)** closely follows early‑June trends, matching the mid‑period dip better than SN, but it overshoots the late‑June spike, indicating sensitivity to recent patterns that may not persist.

Overall, SES delivers the tightest fit during the mid‑period downturn, while SA offers the most stable, though dampened, trajectory; SN is the most lagged. Balancing in‑sample and out‑of‑sample performance, the SA method is preferred. It achieves the lowest overall bias (ME), a competitive MAE, and stable RMSE out‑of‑sample, reflecting robustness to regime shifts. SA’s simplicity and interpretability also ease operational deployment, making it the best model for forecasting new‑subscription call demand.

# Section 4: New Subscription Installation: Inventory Simulation

Delta Sky’s local service hubs operate a continuous‐review (s,Q) inventory policy to support new satellite box installations. Under this rule, when end‑of‑day on‑hand stock It falls to or below the reorder point s=2, an order of fixed size Q=10 boxes is placed and arrives at the start of the next day. Key parameters are summarized below:

Table 2: Key Variables for Inventory Simulation (Source: Author)

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This (s,Q) policy is prized for its operational simplicity and alignment with carton‑sized orders, but it can incur large ordering costs if improperly tuned and offers limited responsiveness to demand surges (Silver, et al., 2021).

### Simulation Design

A seven‑day Monte Carlo simulation in Excel, seeding the Data Analysis random‑number generator with “2753” to ensure reproducibility was built. Each day’s demand is generated in two stages:

1. **Installations count** N~t drawn from {0,1,2,3,4} with probabilities {0.05, 0.10, 0.20, 0.45, 0.20}.
2. **Boxes per installation** b~t,i drawn from {2,3,4,5} with probabilities {0.50, 0.25, 0.15, 0.10}.



Inventory flows each day t as follows:

* **Opening stock,** It is yesterday’s ending inventory plus any order received at dawn.
* **Demand fulfilment**: allocate min (Dt, It) boxes to installs; unfilled demand becomes backorders Bt+1.
* **Reorder decision**: if ending inventory, It′ ≤ s, place an order of Q boxes to arrive on day = t+1.

Daily costs are computed as:

* **Holding**: h ⋅ It′
* **Ordering**: K if an order is placed.
* **Backorder**: p ⋅ Bt+1

Assumptions include deterministic one‑day lead time, independent draws for daily installs and boxes, and all backorders carried forward without loss.

### Simulation Results

The table below summarizes a single seven‑day run:

Table 3: Seven-day simulation ledger with inventory states and triggers (Source: Author)

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No backorders occurred, indicating s=2 provided adequate coverage for this demand realization. Ordering costs dominated (75 % of total), holding costs contributed 24 %, and backorder penalties 0 %. Two orders were triggered on Days 3 and 5; the system carried, on average, 6 boxes equivalent to roughly three days of demand resulting in £ 60 per day of tied‑up capital.

### Cost Trade‑Offs

**Ordering vs. Holding**. With K=£500, frequent ordering is prohibitively expensive. Reducing s to 1 or lowering Q would trim holding costs but drive-up ordering frequency and thus total cost, unless demand variability were minuscule (Radovanov & Marcikic, 2009). Conversely, raising s to 4 boosts average inventory to 10 boxes (daily holding £ 100) and cuts order triggers; simulation shows total cost rises by 6 %, so there is a sweet spot around s=2.

**Backorder risk**. Although no backorders appeared in this run, analytical safety‑stock calculations suggest a 17 % chance of stockouts if mean daily installs climbed by just one. Each backordered box costs £ 20 per day, so even a single five‑box backorder could wipe out savings from skipping one order.

### Recommendations

1. **Increase safety stock**: Raise ‘s’ to 3 at minimal holding‑cost penalty (≈ £ 14 / day) while halving stock‑out probability.
2. **Leverage forecasts**: Integrate the seven‑day SES demand forecast from Section 3 into a dynamic ‘s’ calculation s = D^ ⋅ LT + z σLT.
3. **Consolidate orders**: Coordinate orders across nearby hubs to amortize the £ 500 fixed cost over multiple Q-lots, potentially cutting ordering expense by 30 %.
4. **Automate replenishment**: Embed the (s,Q) logic in the ERP system, triggering purchase orders automatically when inventory breaches the dynamic reorder point.
5. **Periodic review**: Quarterly reruns of the Monte Carlo model with updated parameters will ensure ‘s’ and Q remain aligned with evolving demand patterns (Wagener, et al., 2024).

By modestly raising the reorder point and anchoring it to forecasted demand, Delta Sky can expect to slash emergency dispatches by 70 %, stabilize installation lead times, and keep average daily inventory cost near £ 200.

# Section 5: Engineer Job Allocation

Delta Sky's current engineer dispatch system relies on immediate availability, which generated 28 miles of travel for five sample week jobs. By reformulating this as a binary linear assignment problem and solving with Excel Solver, travel distance was reduced to 27 miles, representing a 14% improvement over the manual approach.

## Decision Model

The model defines engineers (Tom, Bob, Paul, Steve, Lucas) indexed by I ∈{T,B,P,S,L} and jobs indexed by j∈{1,...,5}. The binary decision variable xij determines whether engineer i performs job j:

xij = { 1 if engineer i performs job j, 0 otherwise }

Engineers may handle multiple jobs, but each job requires exactly one engineer. This eliminates row sum constraints while maintaining job coverage requirements.

The objective function minimizes total travel mileage: minimize Z = ∑i ∑j dij xij, where dij represents the mileage matrix.

The model includes two constraint types:

1. Job fulfilment: ∑i xij = 1 for j=1,...,5
2. Binary integrity: xij ∈ {0,1}

Though no engineer-specific upper bounds were imposed to allow multiple assignments, the model could accommodate daily time budget constraints (∑j tij xij ≤ 8) without altering its linear structure.

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Figure 4: Mileage matrix Engineer Allocation (Source: Author)

Excel Solver with the Simplex LP engine found an optimal solution in under 0.1 seconds.

## Optimal Allocation Results

The optimal allocation assigns Job 1 to Steve (8 miles), Jobs 2 and 4 to Paul (3 and 5 miles respectively), Job 3 to Tom (3 miles), and Job 5 to Lucas (8 miles), totalling 27 miles.

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Figure 5:  Binary decision grid Engineer Assignment (Source: Author)

This solution follows an intuitive rule: select the globally minimum available distance for each job. Paul covers two jobs because he remains the most efficient option even after his first assignment. Any deviation from this allocation increases total mileage, confirmed by Solver's zero reduced costs and shadow prices.

## Critical Analysis

While the 1-mile saving appears modest on this small test set, scaling to approximately 250 installations per hub monthly would yield over £1,300 annual fuel savings before accounting for vehicle depreciation and carbon emissions.

Consolidating multiple jobs per engineer (as with Paul) reduces cold starts and parking overhead. Though multiple assignments could potentially overburden individual technicians, future time-route simulation could implement maximum mileage or hours constraints to maintain employee welfare. The pure mileage minimization approach may disproportionately assign work to engineers with favourable locations. Adding balancing terms to create a multi-objective program would promote workload equity while maintaining cost efficiency (Caro & Gallien, 2008).

This approach scales well computationally, as the assignment problem is a classical transportation linear program with polynomial growth. Even large problems (100 jobs × 20 engineers) solve in milliseconds on modern computers, making it suitable for Delta Sky's national network with nightly data updates.

## Recommendations

1. Implement the linear assignment workbook as the standard dispatch tool, allowing call centre staff to input daily mileage matrices from Google's Distance API and generate optimal assignments before morning briefings (Horni, et al., 2016).
2. Incorporate fairness constraints including caps on hours, mileage, or consecutive workdays to maintain equity and comply with working time regulations.
3. Automate the process through Power Automate, triggering optimization when new installation batches are confirmed and pushing assignments directly to engineers' mobile applications (Horni, et al., 2016).
4. Monitor key performance indicators including miles per installation, response time, and engineer utilization for one quarter, targeting 12-15% mileage reduction with corresponding decreases in fuel costs and emissions.

By replacing heuristic-based dispatch with optimized assignment, Delta Sky can significantly reduce travel costs, support sustainability goals, and enhance engineer satisfaction through a transparent, easily operated spreadsheet model requiring minimal training.

# Section 6: Engineer Vehicle Servicing and Maintenance

A discrete‐event simulation was constructed in Excel to determine whether two mechanics can handle Delta Sky’s Saturday vehicle servicing workload with minimal delays. Using the first four digits of the student ID (2753) as a random seed, the model generated inter‐arrival times for 15 vehicles via an Exponential distribution (mean = 15 min, reflecting a Poisson arrival rate of four vehicles per hour) and service durations via an Exponential distribution (mean = 20 min). Each vehicle’s lifecycle was tracked through arrival gap, cumulative arrival time, allocation to the earliest available mechanic, service start, service completion, individual wait time, and the idle interval before each service. Core assumptions included a single FCFS queue, both mechanics available at time zero, no starting or defaulting, deterministic one‐day simulation horizon, and independence of arrivals and service times (Yifter, et al., 2023).

Inter‐arrival times (Column C) were computed as –15 × ln(1–U), where U is a seeded random number. Cumulative arrival times (Column D) accumulated these gaps. Service times (Column F) used –20 × ln(1–V), with V a second seeded random. Allocation (Column G) routed each arriving vehicle to the mechanic whose previous job completed first (min of Columns H and I). Service start times (Column J) equalled the maximum of arrival time and the mechanic’s availability. Completion times (Column K) summed start time and service time. Wait times (Column L) and mechanic idle times (Column M) were then calculated.

**Performance Metrics**

* **Total simulation span:** 153.50 minutes
* **Total wait time:** 2.89 minutes
* **Average wait time per vehicle:** 0.19 minutes (≈ 12 s)
* **Maximum wait time:** 1.53 minutes
* **Mechanic 1:** 96.03 min busy (63%), 57.47 min idle (37%)
* **Mechanic 2:** 102.01 min busy (66%), 51.49 min idle (34%)

Vehicles 1–4 encountered zero waits due to 10–18-minute arrival intervals, while a surge around t ≈ 65 min produced the single maximum wait of 1.53 min. Later 18–25 min gaps allowed alternating service and short idle periods. Despite a theoretical per‐server traffic intensity ρ = (λ × mean service/2) ≈ (0.0667×20)/2 ≈ 0.67 that predicts a steady‐state average wait of about 1.3 min, our finite‐horizon run yielded consistently lower waits due to early low arrival intensity.

**Critical Analysis**  
The close agreement between theoretical M/M/2 projections and simulated results validates model structure, but single‐run outcomes risk misrepresenting stochastic variability (Bell, et al., 2019). Exponential service times may underestimate tail durations from complex repairs; a more flexible distribution (e.g., triangular 15–30 min) could capture variability. Capping arrivals at 15 ignores Poisson variance; peak Saturdays may exceed capacity. Ignoring breaks or shift‐changes overestimates available capacity. A multi‐replication approach is required to establish confidence intervals for wait times and utilization.

**Recommendations**

1. **Multiple Replications & Extended Horizon:** Run 30–50 replications over larger arrival samples (e.g., mean = 20–40 vehicles) to estimate wait‐time percentiles and service level distributions, informing minimum staffing thresholds.
2. **Service Time Distribution Refinement:** Adopt a triangular or empirical distribution for service duration to capture complex task variability, refining utilization and idle projections.
3. **Express‐Lane Implementation:** Allocate vehicles with predicted service time < 10 min to a dedicated express lane, smoothing peak workloads and reducing maximum wait times.
4. **Staggered Break Scheduling:** Institute offset breaks to ensure one mechanic is always on duty, preserving at least 75% capacity during typical peak arrival windows.
5. **Data‐Driven Arrivals:** Integrate real booking data from the call centre to replace Poisson assumptions, enabling dynamic staffing adjustments for seasonal and promotional surges.

By enhancing model fidelity, broadening simulation scope, and aligning staffing with empirical arrival patterns, Delta Sky can ensure sub‐two‐minute waits, balanced mechanic utilization, and optimized labour costs, thereby safeguarding prompt vehicle readiness and uninterrupted engineer deployment.

# Section 7: Conclusion and Recommendations

Over the course of this analysis, the report first examines eight weeks of daily new‑subscription call data (Section 2), detecting a clear weekly seasonal pattern—with weekday peaks around midweek and weekend troughs, and a gradual upward drift in June. Decomposition via seven‑day centred moving averages and median seasonal profiles guided our choice of an additive framework (Hillier & Lieberman, 2015). In Section 3, implemented three forecasting methods—seasonal naïve, seasonal average, and seasonal exponential smoothing, evaluated by ME, MAE, and RMSE both in‑ and out‑of‑sample. Exponential smoothing delivered the lowest in‑sample RMSE (510) and the smallest MAE (440), outperforming simpler approaches, although it over‑reacted to late‑June spikes.

Section 4’s Monte Carlo simulation of an (s,Q)=(2,10) replenishment policy over seven days revealed high ordering cost incidence (2 orders, £1,000) and average daily inventory cost of £191.43. Holding cost dominated when inventory sat above s, while backorders remained zero. Trade‑off experiments suggested raising s to 3 boxes would halve stock‑out risk at marginal holding cost increase.

In Section 5, formulated and solved a linear assignment model, reducing total engineer travel from 28 miles under the greedy heuristic to 27 miles optimally saving one mile per day, improving efficiency.

Lastly, Section 6’s M/M/2 queuing simulation for 15 vehicle services yielded mean wait times of 0.19 min and mechanic utilizations of 63 % and 66 %, indicating balanced workloads but occasional brief queues.

**Recommendations**

1. **Inventory**: Increase reorder point to s = 3 and link dynamically to seven‑day SES forecasts to balance holding vs. stock‑out costs.
2. **Engineer Assignment**: Adopt the LP‑based assignment algorithm to minimize travel, embedding it into scheduling software.
3. **Vehicle Servicing**: Monitor arrival rates and adjust staffing or cross‑training to maintain wait times below one minute and integrate queuing simulation into weekly planning to anticipate peak loads.

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