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1. Introduction

This report supports Delta Sky Broadcasting (DSB) in addressing key operational challenges through data-driven decision-making. The **purpose** is to evaluate performance across forecasting, inventory control, job allocation, and queuing, using applied analytics to drive measurable improvements in efficiency and service quality.

The analysis begins by decomposing the time series of historical call data, followed by forecasting subscription enquiry volumes. This revealed that a seasonal exponential smoothing model was the most accurate and is therefore recommended for anticipating peak demand periods, allowing to align resources further in the analysis. In inventory management, simulation revealed high backorder costs with high ordering frequency under the current system. An EOQ-based policy with an increased reorder point delivered lower total costs and improved inventory stability.

The fifth section applied Linear Programming (LP) to optimise engineer job allocation. This approach reduced travel distance compared to the existing manual method, suggesting a scalable improvement in route efficiency. Finally, a queuing simulation of vehicle servicing highlighted the system's sensitivity to long service times. Strategies such as staggered bookings, triage, and real-time tracking were recommended to reduce bottlenecks.

The report overall recommends adopting LP for routing, EOQ-based inventory control, demand-driven forecasting, and flexible queue management to enhance DSB's overall operational performance while managing resources more effectively.

2. Investigating New Subscription Call Demand

In the broadcasting industry, acquiring new customers is crucial for maintaining competitive advantage (Maringa, 2016). Since consumers are often hesitant to switch service providers, DSB needs to ensure it capitalises on every new subscription opportunity (Andonova, Anaza and Bennett, 2021). To support strategic decision-making and operational planning, this section explores patterns in the daily volume of new subscription calls from May 1 to June 25, 2023.

The data shows a recurring weekly pattern with a noticeable increase in activity in early June. To better understand the underlying trend, a smoothing technique was applied using a centred moving average (CMA).

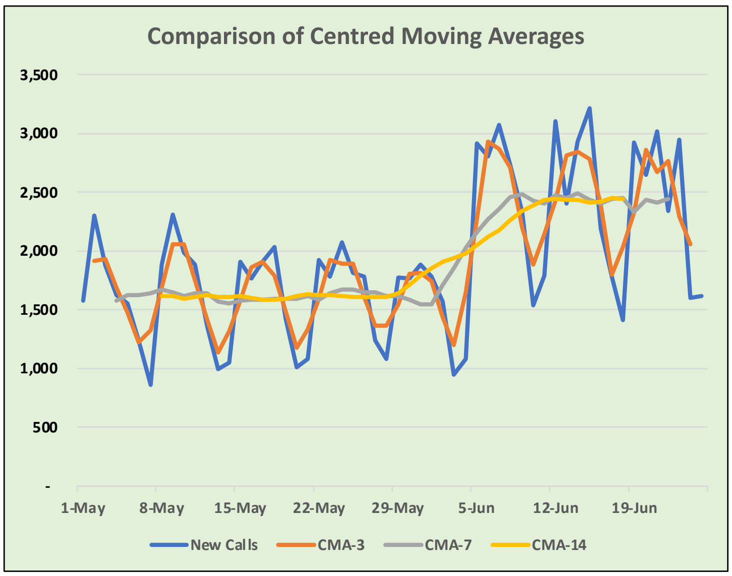

Figure 1: Comparison of Centred Moving Averages and Actual Data (Source: Author)

Three different CMA windows were tested: 3-day, 7-day, and 14-day. The 3-day average was too reactive, capturing noise rather than true trend. The 14-day average, in contrast, over-smoothed the data, masking short-term changes like the early June peak. **CMA-7** provided the most balanced view, aligning with a weekly cycle and effectively smoothing out fluctuations while preserving key features in the data.

The chosen CMA-7 was used to extract the trend component, allowing the identification of a gradual upward trend starting around the end of May. This shift is likely tied to a marketing push or seasonal event that boosted awareness or demand.

To assess seasonality, the data was decomposed using an additive model. This choice was appropriate because the magnitude of seasonal variation remained relatively constant regardless of the overall trend level.

Day	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8
Monday		207.57	328.71	334.86	162.00	754.86	630.43	590.43
Tuesday		658.71	181.71	143.57	180.71	530.71	-49.29	209.43
Wednesday		375.29	324.29	402.00	339.86	720.14	440.43	608.00
Thursday	50.86	246.43	445.00	144.00	235.43	281.86	780.57	-103.57
Friday	-65.86	-277.86	-165.29	131.57	-135.43	-152.57	-212.43	
Saturday	-381.86	-567.86	-587.14	-410.43	-907.29	-884.71	-661.29	
Sunday	-773.57	-502.86	-536.00	-537.71	-940.43	-616.57	-1046.57	

Table 1: Matrix showing detrended values using CMA-7 (Source: Author)

After removing the trend using the CMA-7, the residuals (detrended values) were structured into a matrix by week and day of the week. From this table, the average seasonal effect for each weekday was calculated. The values indicate that call volumes are consistently higher from **Monday to Thursday**, then drop off on **Fridays**, with the **lowest volumes over the weekend**.

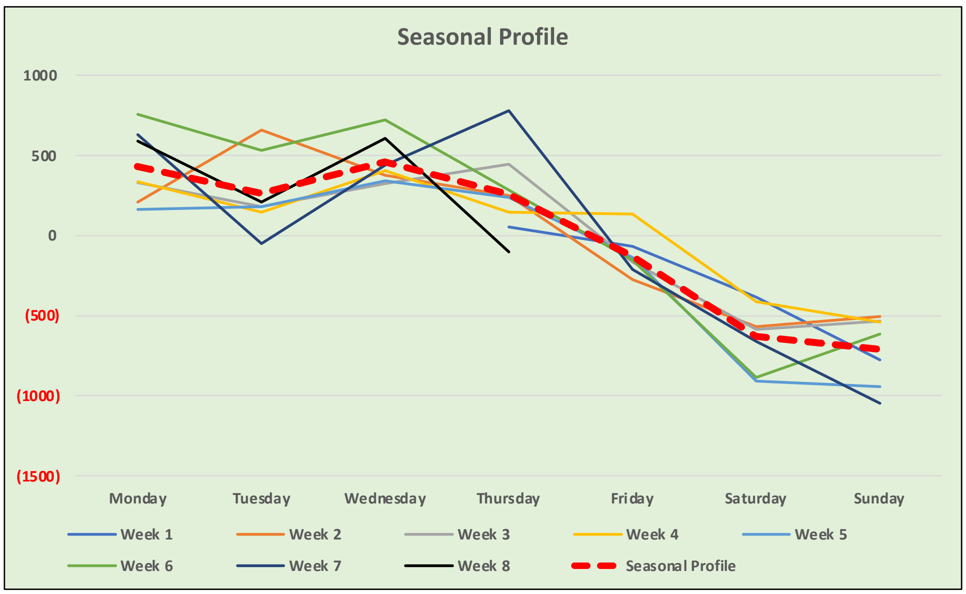

Figure 2:Seasonal Profile and Weekly Patterns across Days (Source: Author)

This weekday-focused pattern also shows that customers are more likely to enquire about subscriptions during the working week. One possible reason is the perception that support, or installation services are limited, slower to respond, or unavailable on weekends, which reduces the likelihood of customer engagement during that time.

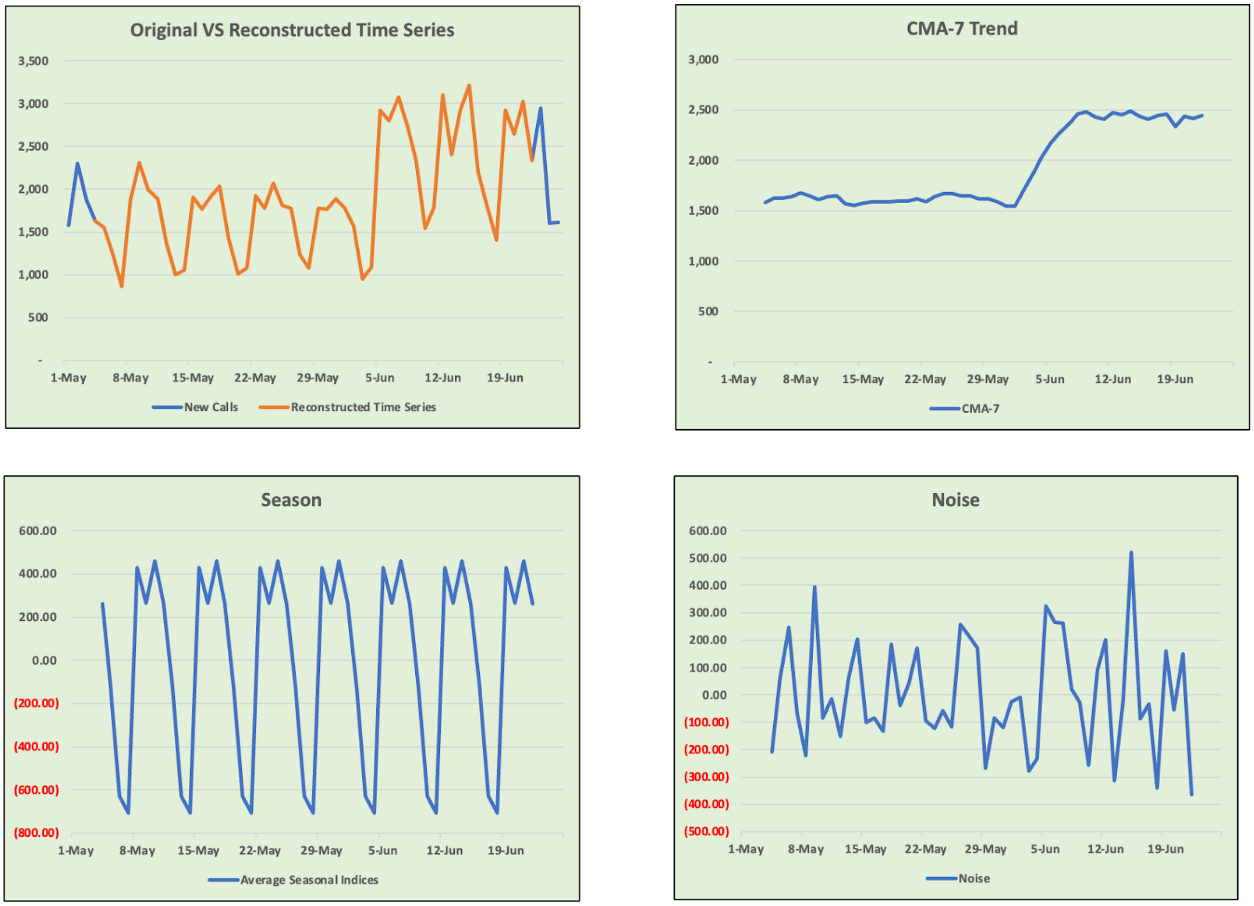

Figure 3: Time Series Components (Source: Author)

These insights carry important operational implications. DSB should align staffing levels and resource availability to match weekday demand, particularly during peak periods such as early June. A flexible resourcing model that increases support capacity from Monday to Thursday could help DSB manage inbound subscription interest more effectively and reduce the risk of missed opportunities.

3. Forecasting New Subscription Call Demand

Forecasting future demand is essential for DSB to manage resources efficiently (Chandran and Khan, 2024). Based on the previously identified trend and seasonality, three models were developed using data from 1 May to 18 June as training, and 19 to 25 June as a test period. These models were Seasonal Naïve, Seasonal Average, and Seasonal Exponential Smoothing (SES).

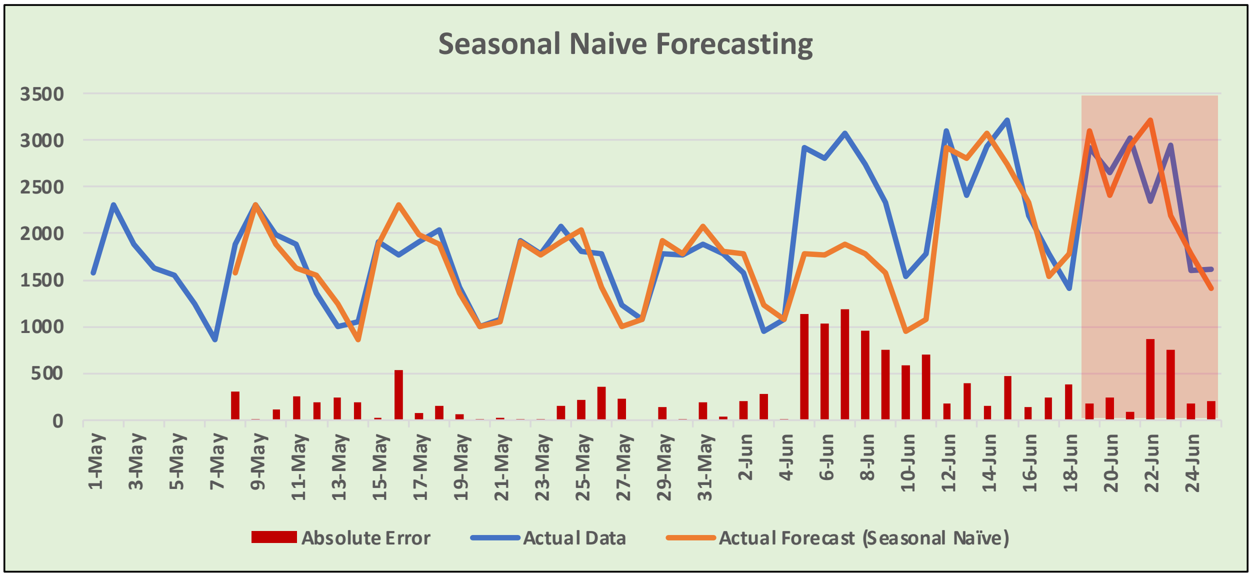

Figure 4: Seasonal Naive Forecasting along with Absolute Error (Source: Author)

The Seasonal Naïve model assumes that demand on a given day will match that of the same weekday from the previous week. While simple, this method is unable to react to sudden changes in trends. During early June, when a noticeable increase in call volume occurred, the model significantly underperformed.

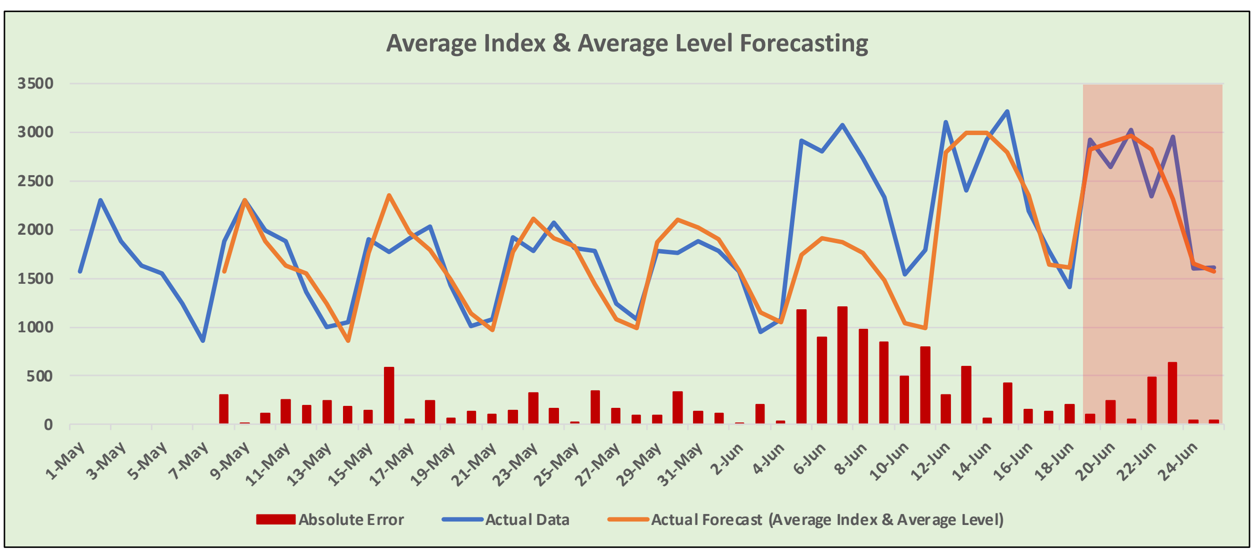

Figure 5: Average Index & Average Level Forecasting along with Absolute Error (Source: Author)

On the other hand, the Seasonal Average model uses a fixed average level combined with day-specific seasonal indices calculated across the training period. Although this model captures the consistent weekly pattern in demand more effectively than the naïve method, it fails to respond to recent upward shifts. As a result, it also displayed forecast errors that limited its reliability for short-term planning.

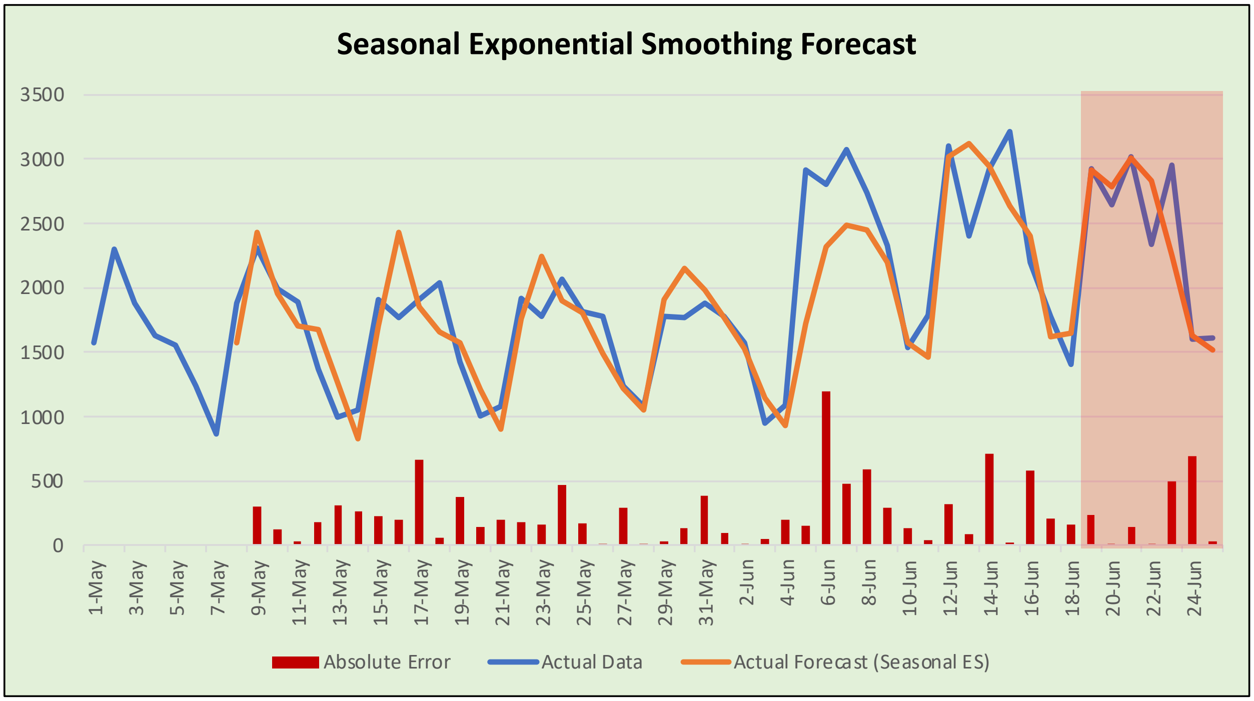

Figure 6:Seasonal Exponential Smoothing Forecasting along with Absolute Error (Source: Author)

In contrast, the **SES** model provided the most accurate results. By assigning more weight to recent observations, it dynamically adapts to both seasonal and trend-related changes. The model performed best with smoothing parameters of α = 0.30 for level and γ = 0.35 for seasonality. This approach successfully tracked recent demand increases while preserving weekday-specific patterns.

Forecasting Model	In Sample Errors			Out Sample Errors		
	ME	MAE	RMSE	ME	MAE	RMSE
Seasonal Naïve	**142.55**	**295.17**	**432.15**	**9.14**	**362.29**	**464.97**
Seasonal Average	262.36	364.30	504.75	597.45	597.45	676.35
Naive Index & Weekly Average Level	142.55	295.17	432.15	9.14	362.29	464.97
Average Index & Average Level	**142.55**	**311.82**	**440.12**	**9.14**	**231.42**	**321.61**
Average Index & MA7 Level	194.02	319.65	458.91	-17.88	327.56	383.26
Seasonal Exp. Smoothing (α=0.30, γ=0.35)	**49.58**	**249.75**	**340.53**	**21.28**	**211.70**	**329.40**
Season-Trend Exp. Smoothing (α=0.50, β=0.20, γ=0.60)	-24.94	256.28	34.61	135.05	254.57	371.35

Table 2: Matrix displaying the In-Sample and Out-of-Sample Error across models (Source: Author)

Forecast performance was assessed using Mean Error (ME), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). Each measure served a specific purpose as ME revealed forecast bias but could hide large errors due to offsetting values. MAE averaged error size but treated all equally. RMSE emphasised larger errors, making it ideal for spotting major inaccuracies.

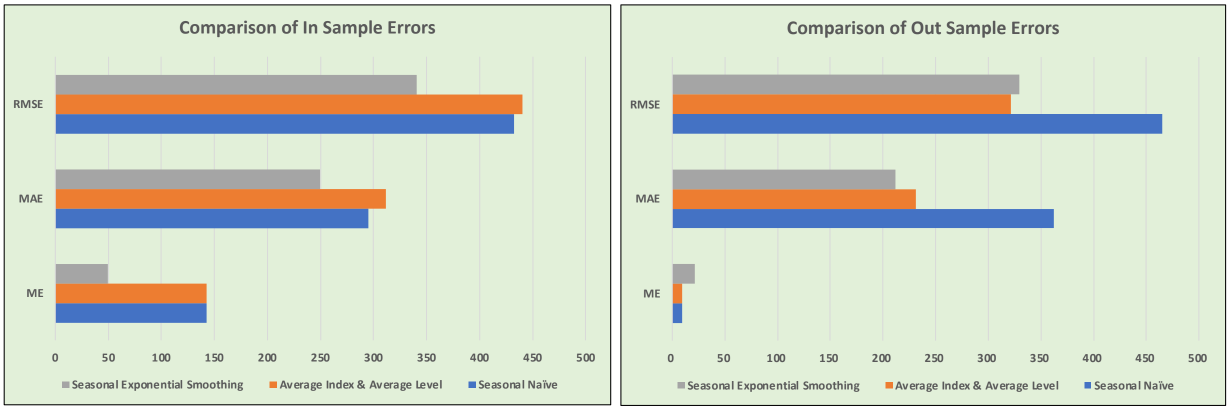

Figure 7: Comparison of Errors across models (Source: Author)

Across both in-sample and out-of-sample data, **SES** had the **lowest error** values across most metrics compared to the other two models. Its responsiveness and adaptability make it the most appropriate model for operational forecasting and managing upcoming subscription-related workloads.

4. New Subscription Installation – Inventory Simulation

DSB uses a **Continuous Inventory System**, which involves monitoring stock levels daily and triggering replenishment once inventory drops to a predefined threshold (Kumar, Kumar and Saha, 2022). In this setup, the Reorder Point (ROP) is set at 2 units, meaning a new order is placed whenever stock reaches or falls below this level. The Reorder Quantity (ROQ) is fixed at 10 units, and inventory begins at 10 units. There is no lead time as orders placed at the end of the day arrive the following morning. Alongside these operational parameters, the system also accounts for costs: a fixed ordering cost incurred whenever an order is placed, a holding cost for storing unused inventory, and a backorder penalty for failing to meet daily demand due to stockouts.

The system offers flexibility and quick response to changes in demand, allowing DSB to replenish stock efficiently. However, it comes with trade-offs between ordering and holding costs as frequent small orders raise ordering costs, while higher inventory increases holding costs. To assess this balance, a 7-day simulation was run using daily demand values generated from the given discrete distributions.

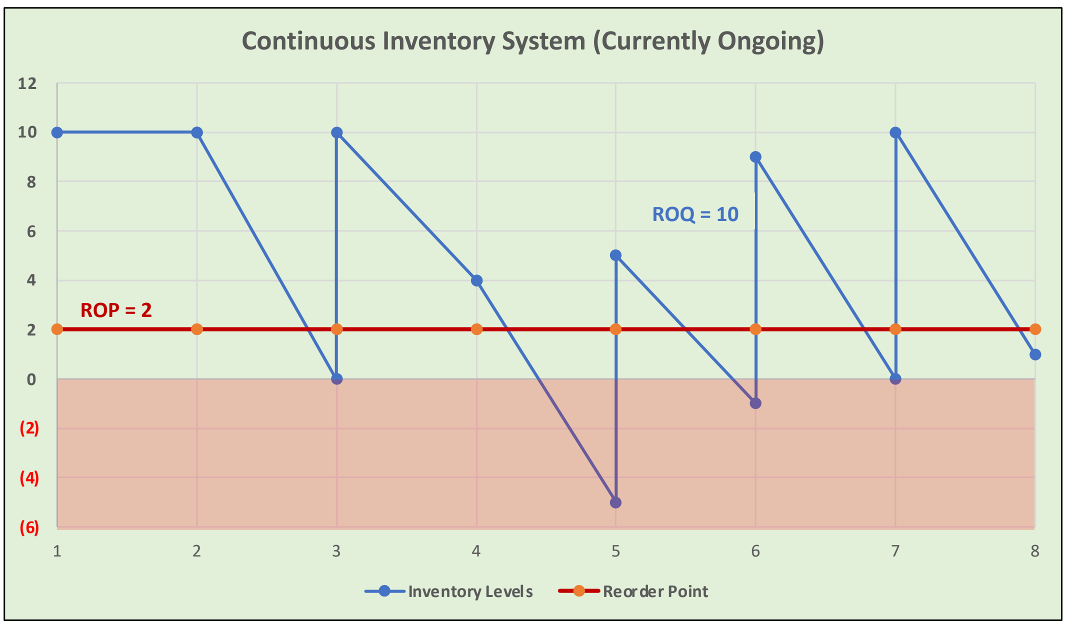

Figure 8: Current Continuous Inventory System (Source: Author)

During the simulation, inventory fell to the reorder point three times, prompting new orders. This suggests the current ROQ of 10 may be **too low** to handle demand spikes, and that **adjusting the ROP** or increasing the order size could reduce the risk of stockouts.

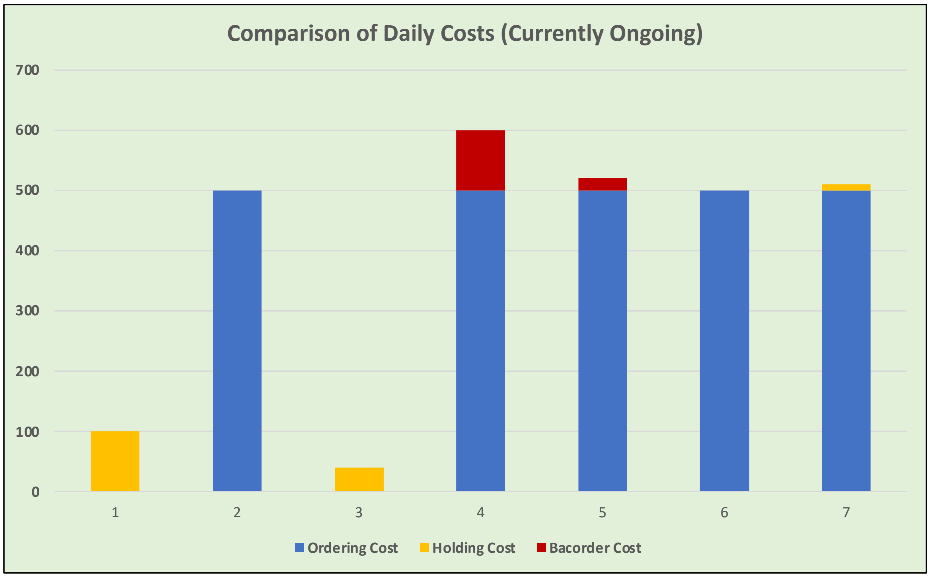

Figure 9: Comparison of Current Daily Costs (Source: Author)

Despite the frequent reorders, backorders occurred on Days 4 and 5, again raising concerns about the adequacy of both the reorder point and the quantity. The cost breakdown reveals that ordering costs are consistently high, while backorder costs are non-negligible, particularly when stockouts occurred. This suggests that the system may benefit from ordering more units on the same day to reduce order frequency and also eliminate unfulfilled demand.

$$
\begin{aligned}
\text{Economic Order Quantity (EOQ)} &= \sqrt{(2 \times \text{Cumulative Demand Rate} \times \text{Ordering Cost}) / \text{Holding Cost}} \\
&= \sqrt{(2 \times 1.29 \times 500) / 10} \\
&= 11.33 \\
&\approx 11 \text{ units}
\end{aligned}
$$

Equation 1: Economic Order Quantity calculation (Source: Author)

To improve inventory performance, an Economic Order Quantity **(EOQ)** approach was applied, resulting in a revised **ROQ of 11 units**. The EOQ method helps minimise the combined cost of ordering and holding by optimising order quantity based on demand and cost parameters. The reorder point remained unchanged at 2 units.

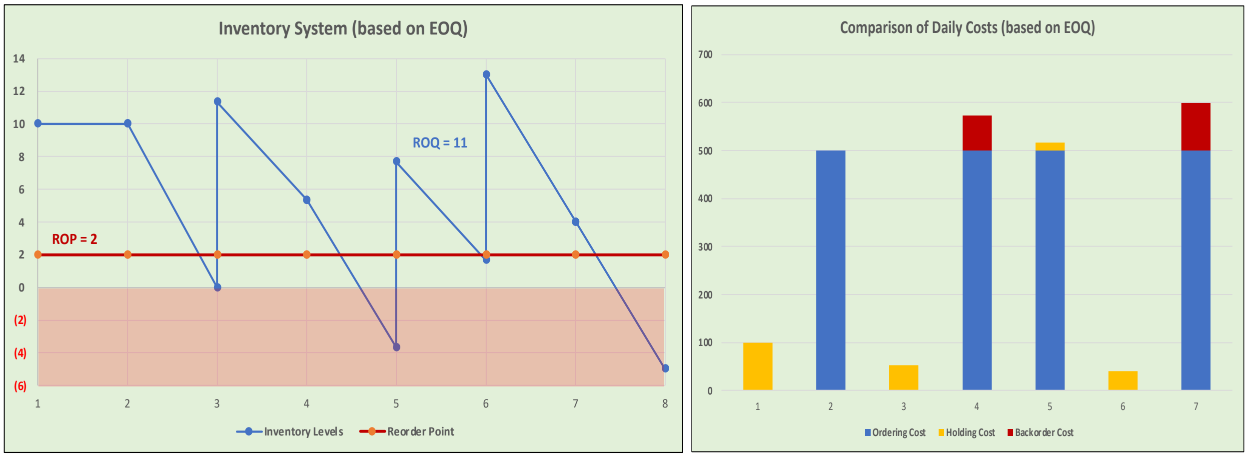

Figure 10: EOQ based Continuous Inventory System and Error Comparison (Source: Author)

Following the implementation of the updated ROQ, a second simulation was run over the same seven-day period. Stockouts were reduced, though backorders still occurred late in the week. Inventory levels remained more stable, with higher safety stock after each delivery to buffer against demand surges.

Holding costs rose slightly due to increased inventory, but this was offset by fewer severe shortages and a more balanced replenishment pattern. Ordering costs were still significant but occurred less frequently. Most notably, the total cost of backorders declined compared to the original set-up.

Overall, the revised ROQ improved stock availability and service consistency. However, since some backorders persisted, further adjustments, such as raising the ROQ or adding safety stock, may be necessary to ensure a more robust system.

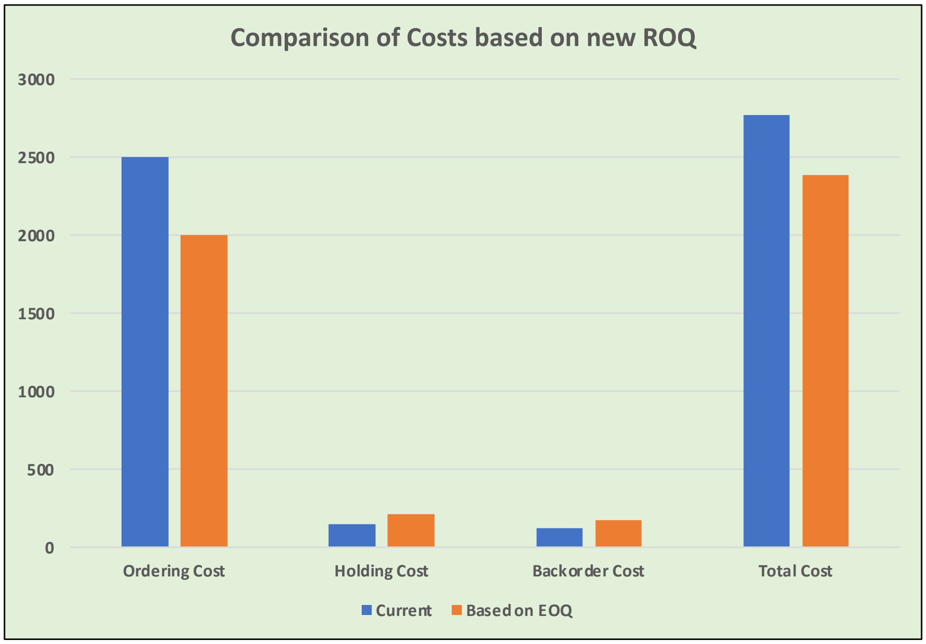

Figure 11: Comparison of Current vs EOQ based costs (Source: Author)

To compare the two set-ups, a cost summary was prepared using data from both the original and EOQ-based simulations. The results show that while the EOQ approach slightly increased holding costs, it successfully lowered overall costs by reducing the frequency of orders and mitigating backorders. Specifically, total costs **under the EOQ configuration** were consistently lower than under the original ROQ of 10 units.

Current ROP	Ordering Cost	Holding Cost	Backorder Cost	Total Cost
0	**2000**	**150**	**120**	**2270**
1	2500	150	120	2770
2	2500	150	120	2770
3	2500	150	120	2770
4	2500	200	20	2720
5	2500	290	0	2790
6	2500	290	0	2790
7	2500	290	0	2790
8	2500	290	0	2790
9	2500	390	0	2890

ROP after EOQ	Ordering Cost	Holding Cost	Backorder Cost	Total Cost
0	2000	170	319	2489
1	2000	170	319	2489
2	2000	210	173	2383
3	2000	210	173	2383
4	2000	210	173	2383
5	**2000**	**274**	**73**	**2347**
6	2000	351	0	2351
7	2500	351	0	2851
8	2500	464	0	2964
9	2500	464	0	2964

Table 3: Matrices comparing different costs based on current and new ROP (Source: Author)

While the EOQ-based configuration with ROQ = 11 and **ROP = 5** delivered the lowest total cost (£2347), it’s worth noting that under the original set-up, a ROP = 0 yielded the lowest cost in that set-up (£2270). However, operating with no safety stock is inherently risky. A sudden spike in demand could lead to significant backorders, driving up shortage costs and negatively impacting customer satisfaction.

In contrast, the current ROP = 2 under the original configuration leads to higher total costs (£2770), largely due to repeated stockouts and increased order frequency. Although the EOQ configuration slightly raises holding costs, it achieves better stability with fewer reorders and more predictable inventory levels. Raising ROP beyond 5 eliminates backorders but inflates holding costs sharply. Therefore, the **EOQ set-up with ROP = 5** offers the best trade-off between service continuity, cost control, and operational resilience.

5. Engineer Job Allocation

DSB currently assigns customer installation jobs to engineers using a manual assignment approach. This method selects the closest engineer for each job in a step-by-step manner, but it doesn't consider whether the overall distance is truly minimised. In this case, the company's manual allocation led to a total travel distance of **28 miles** across five jobs and five engineers as shown in the tables below.

Engineer/Customer	Job 1	Job 2	Job 3	Job 4	Job 5
Tom	14	7	**3**	7	27
Bob	20	7	12	**6**	30
Paul	10	**3**	4	5	21
Steve	**8**	12	7	12	21
Lucas	13	25	24	26	**8**

Initial Total Distance
28

Table 4: Initial Job Allocation and Total distance (Source: Author)

To identify a more efficient allocation, a **Linear Programming (LP)** model was developed with the objective of minimising the total distance travelled. Unlike the manual method, LP evaluates all possible combinations simultaneously to determine the most efficient assignment based on total distance. To construct the LP model, a **binary decision variable** was defined as follows:

$$\boldsymbol{a_{pq}} = \begin{cases} 1 \; when\ engineer\ '\boldsymbol{p}'\ is\ assigned\ to\ the\ job\ '\boldsymbol{q}' \\ 0 \; when\ engineer\ '\boldsymbol{p}' is\ not\ assigned\ to\ the\ job\ '\boldsymbol{q}' \end{cases}$$

In this equation,
$p \in \{1, 2, 3, 4, 5\}$, displays the following engineers in order: Tom, Bob, Paul, Steve, Lucas.
$q \in \{1, 2, 3, 4, 5\}$, displays the following jobs in order: Job 1, Job 2, Job 3, Job 4, Job 5.

The goal of the model is to minimise the total distance travelled by all engineers. To calculate the total distance, each job's distance is multiplied by its corresponding decision variable $\boldsymbol{a_{pq}}$ and the resulting values are summed to account for all possible combinations. This leads to the following **objective function**:

$$Minimise\ Distance = 14a_{11} + 7a_{12} + 3a_{13} + \cdots + 26a_{54} + 8a_{55}$$

The above equation can be further polished:

$$Minimise\ Distance = \sum_{p=1}^{5}\sum_{q=2}^{5}\left(s_{pq} \times a_{pq}\right)$$

In this equation,
$\boldsymbol{s_{pq}}$ displays the distance required for engineer $'p'$ to reach the job $'q'$.

Constraints:

To ensure the model is realistic and meets operational requirements, two constraints were introduced:

A. Each job must be assigned to exactly one engineer, therefore leading to the equation:

$$\sum_{p=1}^{5} a_{pq} \geq 0$$

B. Engineers can be assigned multiple jobs. This reflects DSB's operational flexibility and therefore no upper limit is applied to each engineer, leading to the equation:

$$\sum_{q=1}^{5} a_{pq} = 1$$

Objective Cell (Min)

Cell	Name	Original Value	Final Value
$G$7		27	27

Variable Cells

Cell	Name	Original Value	Final Value	Integer
$B$10:$F$14				
$B$10	Tom Job 1	0	0	Binary
$C$10	Tom Job 2	0	0	Binary
$D$10	Tom Job 3	1	1	Binary
$E$10	Tom Job 4	0	0	Binary
$F$10	Tom Job 5	0	0	Binary
$B$11	Bob Job 1	0	0	Binary
$C$11	Bob Job 2	0	0	Binary
$D$11	Bob Job 3	0	0	Binary
$E$11	Bob Job 4	0	0	Binary
$F$11	Bob Job 5	0	0	Binary
$B$12	Paul Job 1	0	0	Binary
$C$12	Paul Job 2	1	1	Binary
$D$12	Paul Job 3	0	0	Binary
$E$12	Paul Job 4	1	1	Binary
$F$12	Paul Job 5	0	0	Binary
$B$13	Steve Job 1	1	1	Binary
$C$13	Steve Job 2	0	0	Binary
$D$13	Steve Job 3	0	0	Binary
$E$13	Steve Job 4	0	0	Binary
$F$13	Steve Job 5	0	0	Binary
$B$14	Lucas Job 1	0	0	Binary
$C$14	Lucas Job 2	0	0	Binary
$D$14	Lucas Job 3	0	0	Binary
$E$14	Lucas Job 4	0	0	Binary
$F$14	Lucas Job 5	1	1	Binary

Constraints

Cell	Name	Cell Value	Formula	Status	Slack
$B$15:$F$15 = 1					
$B$15	Job 1	1	$B$15=1	Binding	0
$C$15	Job 2	1	$C$15=1	Binding	0
$D$15	Job 3	1	$D$15=1	Binding	0
$E$15	Job 4	1	$E$15=1	Binding	0
$F$15	Job 5	1	$F$15=1	Binding	0
$B$10:$F$14=Binary					

Table 5: Linear Programming Answer Report (Source: Author)

These conditions were implemented using Excel's Solver. The model was set to minimise the total distance, with the binary decision variables enabled under the solver's settings.

Suggested Job Allocation Distance					
Engineer/Customer	Job 1	Job 2	Job 3	Job 4	Job 5
Tom			3		
Bob					
Paul		3		5	
Steve	8				
Lucas					8

Initial Job Allocation Distances					
Engineer/Customer	Job 1	Job 2	Job 3	Job 4	Job 5
Tom			3		
Bob				6	
Paul		3			
Steve	8				
Lucas					8

Total Distance Required
27

Table 6: Suggested vs Initial Job Allocation and the New Total Distance (Source: Author)

After solving, the LP model returned a total distance of **27 miles**, improving on the manual method by 1 mile. The resulting assignment was slightly different from the original. Notably, Paul was assigned two jobs, while Bob was left without any assignments. This highlights how the LP model can exploit flexible job distribution to achieve a lower total cost, though it may lead to workload imbalances if not managed carefully.

This raises a practical consideration: while LP delivers the optimal distance outcome, it does not inherently ensure fairness in task allocation. In operational settings, factors such as workload distribution, service duration, or scheduling constraints may also need to be considered (Kousiouris, Cucinotta and Varvarigou, 2011). These can be incorporated into the model through additional constraints tailored to DSB’s operational needs.

Even a modest improvement, such as the 1-mile saving observed, becomes impactful when scaled across many assignments. Small reductions in travel time can lower fuel usage, reduce vehicle wear, and give engineers more time to complete additional tasks or avoid customer delays (Wadud, MacKenzie and Leiby, 2016).

It is therefore recommended that DSB adopt LP-based job allocation as part of its operational planning. While manual assignment methods are fast, they lack the optimisation potential of LP. With additional fairness constraints. For example, by capping the number of jobs per engineer, LP can provide both efficiency and equity in assignment.

Overall, LP offers a more adaptive and scalable solution that supports long-term operational efficiency as DSB’s workload continues to grow.

6. Engineer Vehicle Servicing and Maintenance

DSB operates a central servicing hub where two mechanics handle routine maintenance for engineer vehicles on Saturdays. With engineers reporting delays in reaching customer sites, the company initiated a simulation to investigate whether bottlenecks in the current servicing process are contributing to operational inefficiencies.

The simulation was designed to assess how well the existing two-mechanic system copes with real-world variability. Using a Poisson distribution with a mean arrival rate of 4 vehicles per hour, vehicle inter-arrival times were generated to reflect typical Saturday flow. Each mechanic's service time followed an exponential distribution with a mean of 20 minutes, consistent with field service benchmarks. The queue operated under a First-In-First-Out (FIFO) discipline with a finite source, since only a limited fleet is serviced on-site.

Wait Time	
Total Wait Time	191.35
Average Wait Time	12.76
Maximum Wait Time	44.97

Mechanic 1	
Total Idle Time	63.71
Idle Time %	22.52%

Mechanic 2	
Total Idle Time	80.33
Idle Time %	32.37%

Table 7: Calculated Waiting Times and Idle Times (Source: Author)

Wait times were calculated as the difference between arrival and service start, while idle time for each mechanic was derived from gaps between job completions and the start of their next task. The total wait time across all vehicles reached 191.35 minutes, with an average wait of 12.76 minutes and a maximum of 44.97 minutes. Mechanic utilisation was otherwise strong as they were idle for 63.71 minutes (22.52%), while Mechanic 2 was idle for 80.33 minutes (32.37%). These figures suggest high engagement overall, yet the queue still suffered delays, demonstrating the common trade-off between low idle time and rising customer wait times.

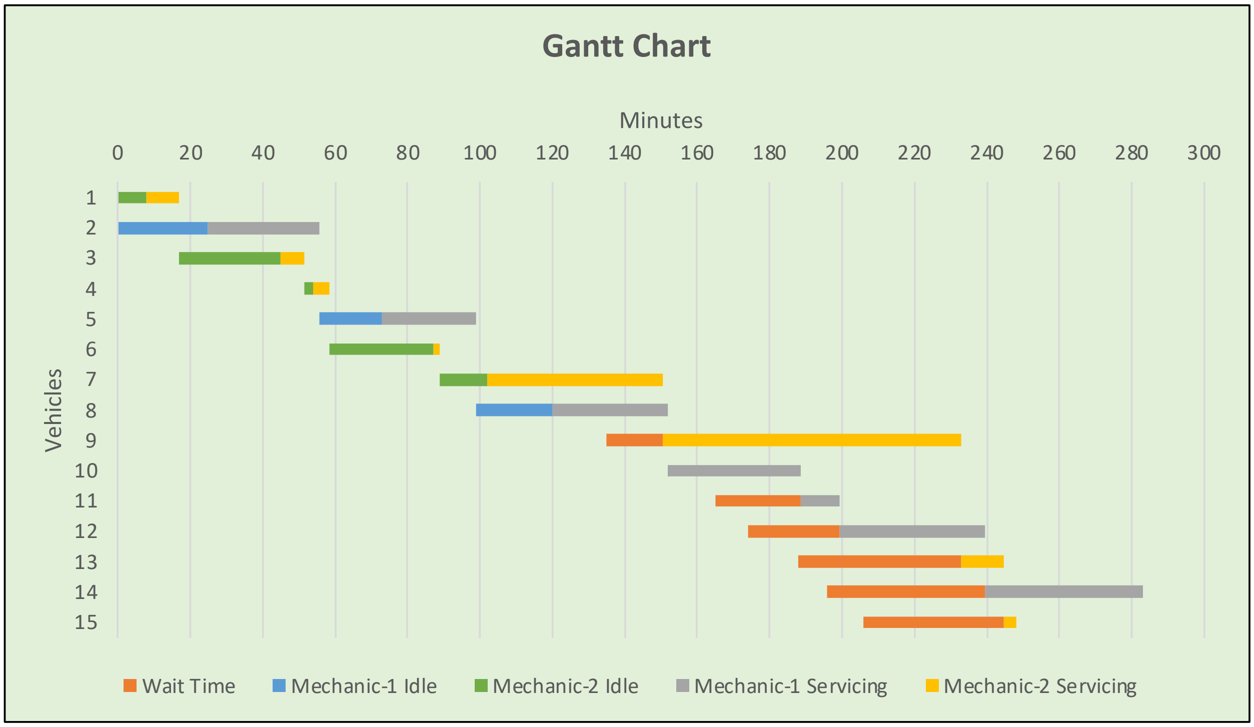

Figure 12: Gantt Chart displaying the servicing, waiting and idle times per mechanic (Source: Author)

The Gantt chart clearly visualises the shift in system performance. The mechanic who became free first was assigned the next vehicle in line. The first half of the day proceeded smoothly, with minimal queuing and balanced mechanic utilisation. However, a significantly longer-than-average service time of 82.46 minutes for Vehicle 9 (handled by Mechanic 2) acted as a critical disruption. With both mechanics occupied, subsequent vehicles began to queue.

The impact of this delay became most evident from Vehicles 10 to 15, where waiting times increased substantially as earlier disruptions compounded. Although mechanic utilisation remained high, the system was unable to recover from this backlog, highlighting a key vulnerability: under stress, efficient resource use alone was not enough to maintain vehicle flow.

The simulation underscores how a single unexpectedly long service duration can compromise the system's balance and create a cascading effect on later arrivals. The model performed adequately under routine demand but lacked resilience when exposed to service time variability. With no flexibility to reprioritise or reallocate vehicles, even a single extreme case led to a backlog.

To address this, DSB should consider operational adjustments that enhance queue stability. Staggered booking slots would prevent arrival bunching and reduce early queue saturation (Huang, Liu and Zhang, 2025). A short triage inspection upon arrival could identify vehicles likely to require extended service, allowing for smarter sequencing (Chowdhury *et al.*, 2023). Prioritising engineers with scheduled customer visits would ensure critical deployments are not delayed, while routine or non-urgent servicing could be rescheduled or deferred (Ilmonen, 2015).

Since adding more mechanics may not be a flexible option, alternative strategies should be considered. Spreading the workload across more than one day or introducing limited mid-week servicing would reduce pressure on Saturday. During inevitable wait periods, engineers could engage in light administrative work or access real-time updates on their vehicle's status to reduce perceived idle time. Additionally, DSB could use internal digital tools to flag jobs with a history of overrunning, helping mechanics anticipate and better allocate time (Ghosh, 2025).

In conclusion, while DSB's current setup performs reliably under typical demand, the simulation revealed a lack of flexibility when faced with unexpected service delays. Even with efficient mechanic utilisation, the system lacked flexibility, resulting in queue build-up and extended vehicle wait times. Rather than expanding staff, DSB can enhance performance by implementing targeted scheduling, prioritisation protocols, and queue smoothing strategies, preserving service quality while controlling cost.

7. Conclusion and Recommendations

This report evaluated four key operational areas at DSB using applied analytics. Based on the findings, here are some recommendations:

- Call volume analysis revealed consistent weekday peaks, and the SES model was found to be the most accurate forecasting method due to its adaptability to both trend and seasonality. DSB should implement this model to support proactive resource planning during high-demand periods.
- In inventory management, simulation showed that the current configuration led to frequent stockouts and elevated backorder costs. An EOQ-based ROQ of 11, combined with a higher ROP of 5, provided better service continuity and reduced total costs, a strategy DSB should adopt while avoiding zero-safety-stock configurations.
- For job allocation, LP improved upon the manual method by reducing travel distance from 28 to 27 miles, suggesting LP should be applied for allocating jobs. Although modest, this efficiency gain is scalable and can be enhanced with fairness constraints to manage workload distribution.
- Finally, the queuing simulation exposed the servicing system's vulnerability to outlier service durations. Targeted scheduling, triage, and real-time job monitoring are suggested as they are critical for preventing bottlenecks without increasing staff.

DSB should integrate these data-driven approaches into its operations to improve cost efficiency, resource allocation, and service quality across its subscription, inventory, and maintenance functions.

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