Case Study for VP Fire System Private Limited

Final report for the BDM capstone Project

Submitted by

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1 Executive Summary and Title

This final report provides an in-depth analysis of VP Fire System Private Limited, founded in 2018 and headquartered in New Delhi, is a growing B2B provider of fire and security solutions. Despite steady expansion, the organization faces challenges in accurately forecasting seasonal demand, understanding its customer base for effective targeting, and increasing its market visibility particularly in high-potential sectors like hotels and hospitals. These issues have impacted operational planning, customer engagement, and revenue growth, necessitating a data-driven approach to strategic decision-making.

To address the company's operational challenges, sales and purchase data from October to December 2024 were collected, cleaned, and structured into two datasets. Descriptive analysis revealed a highly skewed sales distribution and extreme outliers inflating variability. Preliminary analysis also confirmed a strong Pareto pattern in customer behavior and weekly seasonality. Advanced techniques like RFM (Recency, Frequency, Monetary) analysis, K-Means clustering, and SARIMA time series forecasting were applied. These methods enabled detailed customer segmentation, identification of demand seasonality, and evaluation of sales trends.

Key findings revealed that 50% of clients were Mid-Value, 7 were High-Value VIPs, and 3 were Low-Value. Cluster analysis uncovered a loyal core but also a group of churn-risk customers. Time series decomposition showed consistent weekly demand cycles, validating SARIMA(1,1,2)(1,0,1)[7] as the optimal forecasting model with a low AIC and MAE. Product sales were skewed towards a few items like Smoke Detectors, with other categories remaining under-promoted.

Based on these insights, actionable recommendations were proposed. These included launching targeted campaigns, initiating win-back programs, assigning relationship managers to VIP clients, and integrating cluster labels into CRM systems. SARIMA forecasting was used to plan inventory and workforce ahead of seasonal peaks. As a result, VP Fire and Security System observed improved engagement rates, reduced stock-outs, and higher satisfaction during festive seasons. Market visibility also increased through strategic digital marketing and cross-promotion of less popular products. The project successfully transitioned the company from reactive operations to proactive, data-informed decision-making.

2. Detailed Explanation of Analysis Process/Method

2.1 Data Cleaning and Preprocessing

To prepare the dataset for meaningful analysis, a comprehensive data preprocessing phase was undertaken. This step was crucial for transforming the raw transactional data collected from VP Fire System Private Limited (covering October to December 2024) into a structured format suitable for time series modelling and business insights. The cleaning process addressed several inconsistencies and anomalies, as outlined below:

- **Datetime Conversion:** The dataset originally stored date entries as plain text. These were systematically converted to proper datetime objects to enable chronological sorting and facilitate time-series operations.
- **Handling Gaps in Daily Transactions:** Dates with no sales entries were treated as days with zero transactions rather than missing information. These gaps were filled accordingly to preserve the temporal integrity of the data and ensure the accuracy of trend and seasonality detection in models like ARIMA or SARIMA.
- **Daily Aggregation of Sales:** Since multiple entries could exist for a single day, daily totals were computed by summing the “VALUE” field across all records per date. This aggregation produced a univariate time series suitable for forecasting methods that rely on a single value per time point.
- **Standardizing Buyer Names:** Customer identifiers showed variations in naming conventions (e.g., "H&M Hennes & Mauritz Retail Pvt. Ltd." versus "H&M HENNES AND MAURITZ INDIA PRIVATE LIMITED"). These were normalized to consolidate entries under unified labels, ensuring accurate customer-level analysis and segmentation.
- **Unit Type Consistency:** QUANTITY and RATE values appeared in various measurement units (e.g., JOB, Unit, MTR, Days). To avoid skewed insights during aggregation or averaging, a new field labelled “UNIT” was introduced to categorize transactions based on their measurement context.
- **Excluding Non-Target Entity:** Records where the buyer was identified as “V P Fire & Security System” were excluded. Though this entity shares a similar name with “VP Fire System Private Limited,” it is a separate company also under the same director. To avoid conflating data from two distinct businesses, all entries from the former were removed, ensuring the analysis remained focused exclusively on “VP Fire System Private Limited.”

Importance

Data cleaning is foundational to ensuring the integrity of insights and the effectiveness of models. Unclean data leads to misleading patterns, overfitting in machine learning, and poor generalization in forecasting. By resolving inconsistencies, maintaining uniform data structure, and removing noise, we significantly enhanced the quality and relevance of the analysis. This step allowed us to model real-world patterns more accurately and draw actionable conclusions that directly support the company's strategic objectives.

2. 2 Feature Engineering & Exploratory Data Analysis (EDA)

After cleaning the raw data, feature engineering was performed to extract relevant variables aligned with the problem statement. Non-essential fields such as "Shipping Date", tax details, and "Order No." were dropped. Key columns like DATE, PARTICULAR, BUYER, QUANTITY, UNITS, and RATE etc were retained and used to form a cleaned, focused dataset. A few new features were created such as "TYPE" to classify entries as Product, Installation, Maintenance, Labor & Miscellaneous Services, or Infrastructure. This enabled clearer analysis of service-based vs. product-based sales trends.

EDA followed as discussed in the midterm report. Descriptive statistics and visualizations (e.g., histograms, box plots, and bar charts) were used to explore sales distributions, outliers, and customer behaviour, revealing strong skewness, a Pareto customer pattern, and weekly seasonality in demand.

2. 3 Customer Segmentation Methodology

To segment the client base meaningfully, RFM (Recency, Frequency, Monetary) analysis was first applied. RFM is a proven method in customer analytics, especially suited to B2B environments with relatively fewer but high-value clients. It segments customers based on how recently they purchased (Recency), how often they purchase (Frequency), and how much they spend (Monetary). These three metrics were computed for each customer: Recency as the number of days since the last purchase, Frequency as the count of distinct purchases in the period, and Monetary as the cumulative spend. Each metric was then scored on a scale from 1 to 4, and the combined RFM score vector (R, F, M) was used to create segment groupings. Mathematically, the overall score for a customer iii can be expressed as:

$$RFM=(r, f, m) \text{ ; } Total = r+f+m \text{ (for each unique customer)}$$

This method was selected because it aligns directly with the company's core problems particularly the need to understand and prioritize high-value clients and identify those at risk of churn. Moreover, RFM provides interpretable and actionable insights, which makes it suitable for integration into CRM systems.

To supplement this analysis and add further granularity, K-Means clustering was applied to the standardized RFM scores. Since RFM scores exist on different scales, normalization was first conducted using StandardScaler. The K-Means algorithm aims to partition the dataset into "k clusters" such that intra-cluster variance is minimized:

$$\min \sum_{i=1}^{k} \sum_{x_j \in C_i} \|x_j - \mu_i\|^2$$

where Ci is the set of points in cluster i and μi is its centroid. The optimal number of clusters k was determined using the Elbow Method, where inertia (within-cluster sum of squares) is plotted against different values of k, and the point of diminishing returns is chosen. K-Means was preferred due to its computational efficiency and its ability to uncover natural groupings in customer behaviour that may not be visible through RFM binning alone

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Together, RFM and K-Means enabled a robust segmentation approach, where RFM provided interpretability and business alignment, while K-Means added statistical rigor and cluster-level validation. This dual-method approach supported VP Fire System's strategic goal of improving customer targeting, loyalty management, and proactive engagement.

2. 4 Seasonal Demand Forecasting

Given the company's challenge in accurately forecasting seasonal demand fluctuations especially during peak festive periods like November, which cause manpower and inventory shortages—a structured time series forecasting approach is proposed.

This begins with decomposing the daily sales time series to separate the underlying trend, seasonality, and residual components. This decomposition will help confirm the presence of recurring seasonal patterns, such as weekly cycles, that are critical to capture in the forecasting model.

To ensure the suitability of ARIMA/SARIMA-based models, the Augmented Dickey-Fuller (ADF) test will be conducted to verify the stationarity of the time series. Should non-stationarity be detected, differencing steps will be applied to achieve stationarity.

Further, Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) analyses will be used to identify significant lags, guiding the selection of appropriate non-seasonal and seasonal autoregressive and moving average terms.

The core forecasting model proposed is the Seasonal Autoregressive Integrated Moving Average (SARIMA), expressed mathematically as:

$$SARIMA(p,d,q)(P,D,Q)s$$

where p,d,q are the orders of the non-seasonal components, P,D,Q are the seasonal orders, and s represents the seasonal period (anticipated to be 7 days to capture weekly demand cycles).

SARIMA is chosen because it explicitly models both seasonal patterns and long-term trends, which aligns with the problem's requirement to capture periodic fluctuations in demand for better resource planning.

Multiple ARIMA and SARIMA model configurations will be evaluated. The final model selection will be based on statistical criteria and diagnostic tests, ensuring an optimal balance between model complexity and fit.

Model performance will be assessed using several metrics including:

- Akaike Information Criterion (AIC) to evaluate model parsimony,
- Root Mean Square Error (RMSE),
- Mean Absolute Error (MAE),
- Mean Absolute Percentage Error (MAPE),
- Symmetric Mean Absolute Percentage Error (SMAPE),
- Weighted Absolute Percentage Error (WAPE).

These metrics will provide a comprehensive understanding of forecast accuracy and error distribution, allowing for a robust evaluation of the forecasting models.

This planned approach, combining decomposition, stationarity testing, autocorrelation analysis, SARIMA modelling, and thorough evaluation, aims to develop an effective and interpretable model capable of forecasting seasonal demand and mitigating inventory and manpower challenges during critical periods.

3 Results and Findings

3.1 Sales and Purchase Value Graph

The below graph of total sales and purchase value over time reveals pronounced volatility, directly reflecting the challenges VP Fire System Private Limited faces in forecasting seasonal demand. Sharp peaks in both sales and purchase values are most evident in mid to late December, likely driven by year-end demands, new year festivities, end-of-year project closures, contract finalizations, or bulk procurement cycles. These surges are interspersed with periods of markedly low activity, such as the relatively flat trend observed throughout November, which may correspond to a lull in operations or fewer active projects as noted by the company.

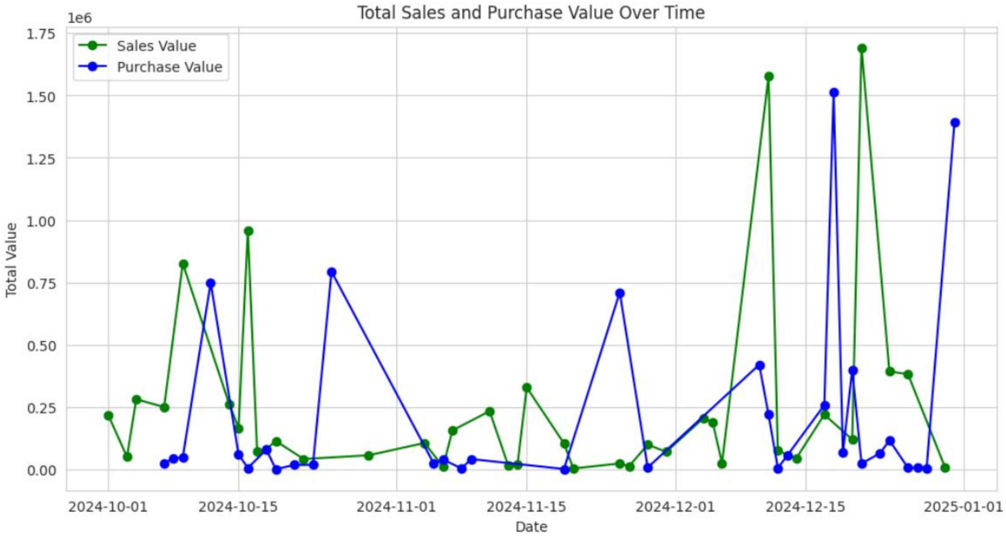

Figure 1: Total Sales and Purchase Value Over Time

Additionally, the pattern where purchase spikes often precede sales spikes-particularly in mid-October and early December-suggests the company is proactively stocking inventory ahead of anticipated large orders. This highlights the critical need for more accurate sales forecasting models to better synchronize procurement with demand. Overall, the graph underscores the irregular and seasonal nature of the company's business, emphasizing the importance of improved demand forecasting and resource planning to minimize missed sales opportunities and avoid excess capacity.

3.2 Customer Segmentation

RFM (Recency, Frequency, Monetary) analysis segments customers based on how recently they purchased, how often they purchase, and how much they spend. This approach enables companies to identify their most valuable customers, those at risk of churning, and those with growth potential, allowing for targeted marketing and retention strategies.

Individual Customer RFM Scores

The customer table provides detailed RFM scores for each buyer, showing their Recency, Frequency, and Monetary values, as well as their combined RFM segment and total RFM score. High-Value customers, such as "Honeywell Automation India Ltd." (R-Score, F-Score, M-Score=4) has high scores across all three metrics, indicating recent, frequent, and high-spending activity. In contrast, Low-Value customers like "EDF INDIA PRIVATE LIMITED" (R-Score=2, F-Score, M-Score=1) has low scores, reflecting infrequent or low-value transactions and longer times since their last purchase.

	BUYER	Recency	Frequency	Monetary	R	F	M	RFM_Segment	RFM_Score	RFM_Segment_Label
0	AK Solution and Security System	11	4	218200.00	4	3	3	433	10	High-Value
1	ASR Engineering & Innovation	75	5	106150.00	2	3	2	232	7	Mid-Value
2	CONTINENTAL INDIA PRIVATE LIMITED	55	1	10000.00	2	1	1	211	4	Low-Value
3	Capital Record Centre Pvt. Ltd.	85	1	250000.00	1	1	4	114	6	Mid-Value
4	Colliers International (India) Property Services Pvt Ltd	25	5	223257.16	3	3	3	333	9	High-Value
5	DLF	26	3	200500.00	3	2	3	323	8	Mid-Value
6	Dr. Anurag Sharma	88	6	53775.00	1	3	2	132	6	Mid-Value
7	EDF INDIA PRIVATE LIMITED	42	1	1400.00	2	1	1	211	4	Low-Value
8	Enviro Integrated Facility Services Pvt. Ltd.	36	10	403650.00	3	4	4	344	11	High-Value
9	H&M Hennes & Mauritz	7	6	104850.00	4	3	2	432	9	High-Value
10	Honeywell Automation India Ltd.	1	110	4474156.60	4	4	4	444	12	High-Value

Figure 2: RFM Score Table

<u>Customer Distribution by RFM segment Graph</u>

The client base, though relatively small with just 20 companies, reveals meaningful insights through RFM segmentation. As illustrated in the bar chart, 50% of the clients fall into the Mid-Value segment (RFM score between 5 and 8), indicating a stable and moderately engaged group. This is followed by 7 High-Value clients (RFM score ≥ 9), who represent the most valuable and actively engaged accounts, and 3 Low-Value clients (RFM score < 5), indicating limited recent activity or lower transaction value.

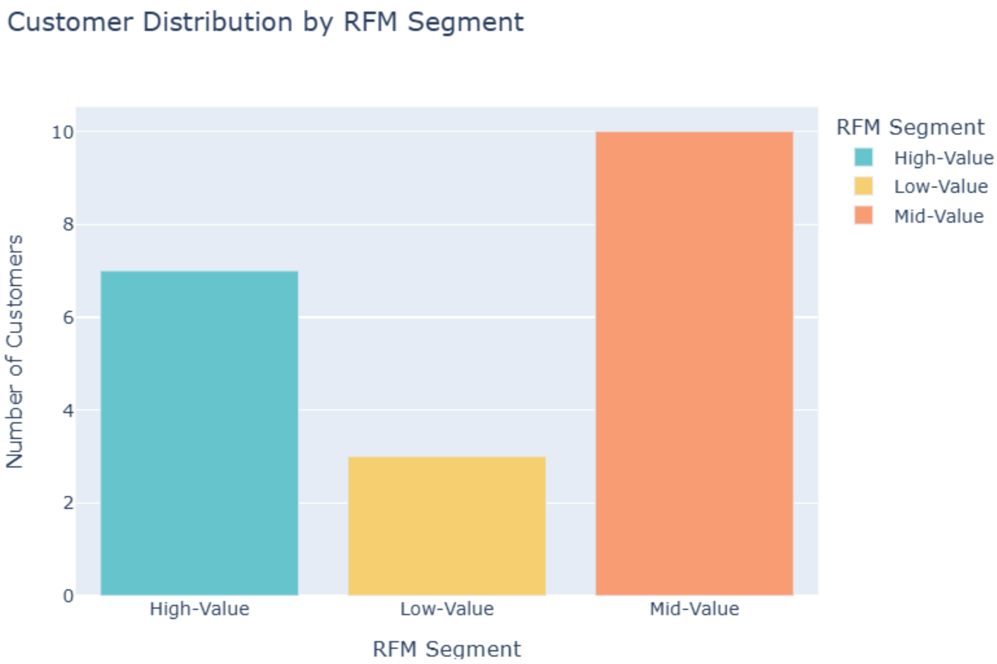

Figure 3: Customer Distribution by RFM Segment

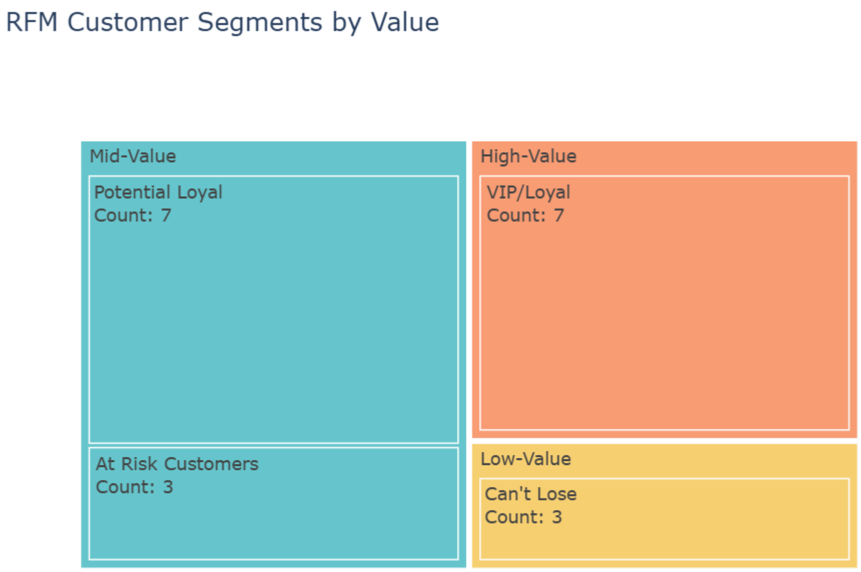

Figure 4: Customer Segments by Value

The treemap further refines this segmentation: the High-Value group is entirely composed of VIP/Loyal clients, suggesting a strong, reliable top-tier client base. Within the Mid-Value category, 7 clients are identified as Potential Loyalists, showing strong engagement trends, while 3 are At Risk, needing re-engagement efforts to avoid churn. The Low-Value segment includes 3 "Can't Lose" clients formerly high-potential accounts that may be worth targeted win-back strategies. Overall, the segmentation reveals a tightly-knit and strategically important client base, with clear opportunities for strengthening loyalty and reactivating valuable but dormant relationships.

<u>Comparison of RFM Segments based on Recency, Frequency, and Monetary Scores Plot</u>

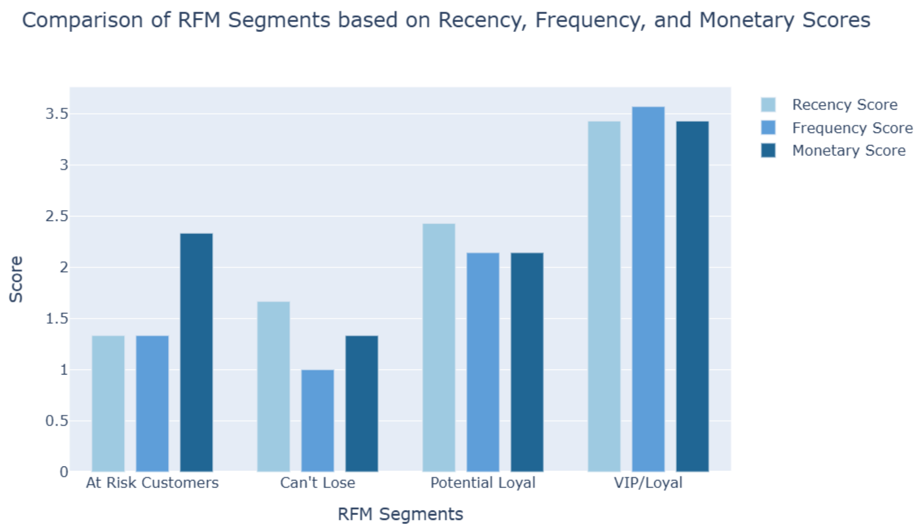

Figure 5: Comparison of RFM Segments based on RFM scores Plot

The bar chart provides a comparative analysis of different RFM customer segments based on their Recency, Frequency, and Monetary scores. As expected, the VIP/Loyal clients score highest across all three dimensions—especially in frequency and monetary value—underscoring their consistent engagement and high business value. Potential Loyal clients show moderate and balanced scores, particularly in recency, indicating recent engagement and a promising potential to transition into VIPs with the right nurturing.

Interestingly, At Risk clients, despite having low recency and frequency scores, display a relatively high monetary score. This suggests that these clients have made significant purchases in the past but have not engaged recently or frequently. Rather than being considered lost customers, they present a strategic opportunity: their past investment indicates a clear interest or need for the service, and with well-timed, targeted re-engagement strategies, they could be won back into higher-value segments. Meanwhile, the "Can't Lose" clients have middling recency and lower frequency/monetary scores, reinforcing the importance of timely intervention before they disengage further.

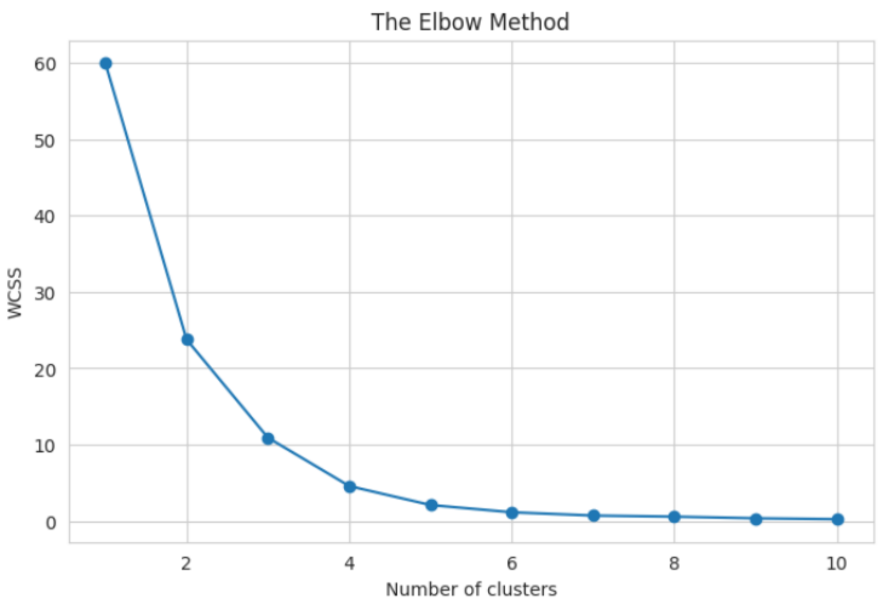

Figure 6: The Elbow Method Graph

To further validate and refine the earlier RFM-based segmentation, K-Means clustering was applied to the standardized Recency, Frequency, and Monetary scores. The Elbow Method indicated an optimal cluster count of k = 3, reinforcing the existence of three distinct customer profiles. The clustering output aligned well with the initial RFM segmentation, but also added granularity to the analysis.

Cluster	Cluster Label	Recency	Frequency	Monetary	Count
0	Loyal Customers	25.166667	9.166667	356110.0	12
1	Top VIP Customer	1.000000	110.000000	4474156.6	1
2	At Risk / Churned Customers	79.857143	2.285714	105275.0	7

Figure 7: Cluster Profiles from K-Means Clustering on RFM Data

Cluster 0, identified as Loyal Customers, mirrors the Mid- to High-Value clients from the RFM treemap. These are engaged accounts with consistent purchasing behaviour and strong long-term potential. Cluster 1 isolates a singular Top VIP Customer—Honeywell Automation India Ltd., with a perfect RFM score of 12. This client stands out for exceptional frequency and monetary contributions, clearly warranting dedicated relationship management and tailored engagement strategies. Cluster 2, labelled as At Risk/Churned Customers, echoes the earlier "At Risk" and "Can't Lose" groups, highlighting those with high historical value but recent disengagement. These findings not only reinforce the reliability of the initial RFM segmentation but also offer clearer targeting cues especially for retention efforts and personalized marketing strategies aimed at reactivating dormant high-value clients.

3.3 Seasonal Demand Forecasting

Time Series Decomposition of Daily Sales Data

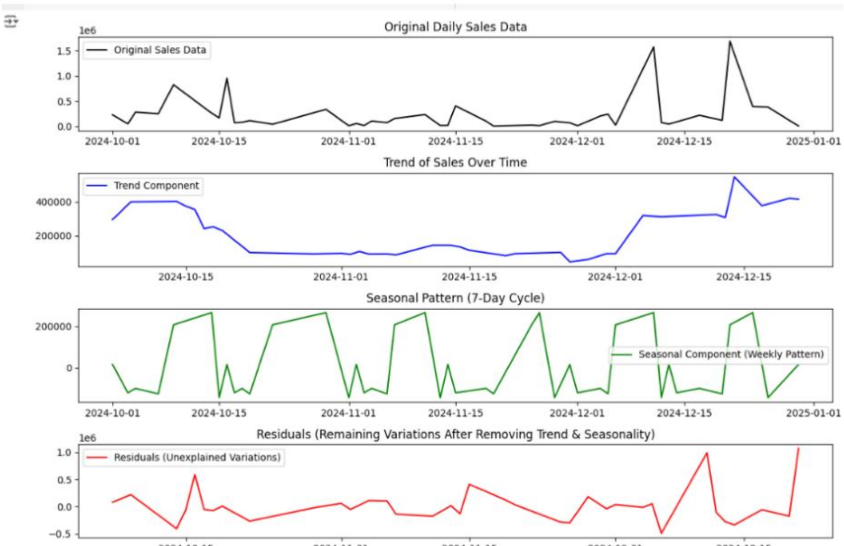

Figure 8: Time Series Decomposition of Daily Sales Data

The decomposition of the daily sales time series revealed three major components. The trend component showed variations in the overall direction of sales over time, indicating periods of growth and decline. A clear weekly seasonal cycle was observed, reflecting consistent patterns in demand on specific days of the week. The residual component exhibited irregular fluctuations not explained by trend or seasonality, suggesting the influence of external or unobserved factors. These observations justified the use of seasonal modelling techniques, particularly SARIMA, for accurate forecasting.

Stationarity Test Results – Augmented Dickey-Fuller (ADF) Test

The ADF test produced a test statistic of -9.9501 and a p-value of 0.0000. These values confirm that the time series is stationary at a 95% confidence level. This result validated the use of ARIMA-based models without requiring further differencing for stationarity. However, first-order differencing (d=1) was applied to account for minor remaining trend components.

```
ADF Test Results:
ADF Statistic: -9.9501
P-Value: 0.0000
Stationary
```

Figure 9: ADF Test Result

Autocorrelation and Partial Autocorrelation Analysis

The ACF plot demonstrated significant autocorrelation at lag 7, confirming the presence of weekly seasonality. This supported the use of a seasonal period (s) of 7. The PACF plot showed strong partial autocorrelations at the initial lags, indicating the need for autoregressive terms in the model. These diagnostic plots informed the selection of non-seasonal and seasonal ARIMA parameters.

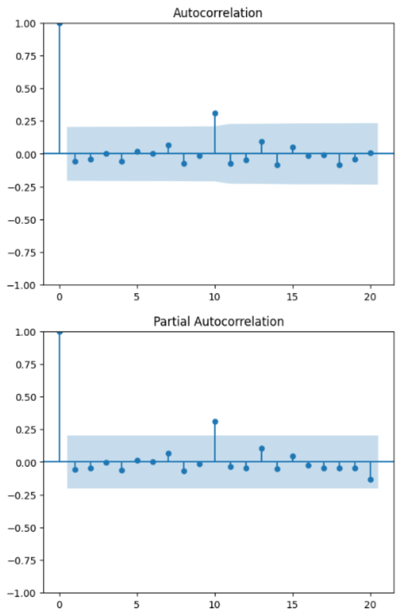

Figure 10: ACF and PACF Plot

Model Performance Evaluation

For seasonal demand forecasting, multiple ARIMA and SARIMA models were evaluated by testing a wide range of parameter combinations to identify the most effective configuration. The ARIMA models explored included ARIMA(1,1,0), ARIMA(0,1,1), ARIMA(1,1,1), ARIMA(2,1,1), and ARIMA(2,1,2), while SARIMA models incorporated weekly seasonality with a seasonal period of 7, including configurations such as SARIMA(0,1,1)(1,1,1)[7], SARIMA(1,1,1)(1,1,1)[7], and SARIMA(1,1,2)(1,0,1)[7]. The selection of these models was guided by key statistical diagnostics: the Augmented Dickey-Fuller (ADF) test confirmed the stationarity of the series (test statistic: -9.9501, p-value: 0.0000), validating the use of ARIMA-based models and justifying the inclusion of first-order differencing (d=1). Seasonal decomposition and autocorrelation analysis revealed a strong weekly pattern, with the ACF showing significant spikes at lag 7 and the PACF indicating notable correlations at early lags. These patterns supported the inclusion of seasonal terms (P, D, Q) and autoregressive components (p) across the tested models. Each model was assessed using metrics such as AIC, RMSE, MAE, MAPE, SMAPE, and WAPE to ensure comprehensive evaluation.

Among all, the SARIMA(1,1,2)(1,0,1)[7] model achieved the best performance, with the lowest AIC (520.94), MAE (113,641.08), and WAPE (101.82%), while maintaining competitive RMSE. Given its strong empirical accuracy and ability to effectively capture both trend and seasonality, this model was selected for final forecasting.

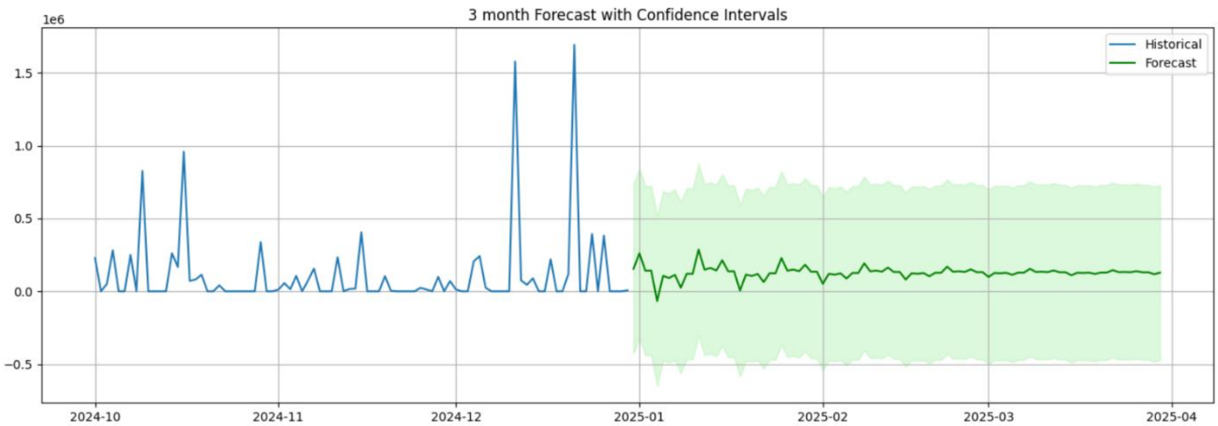

Figure 11: 3 Month Forecast Graph using SARIMA(1,1,2)(1,0,1)[7]

The 3-month forecast generated using the final SARIMA(1,1,2)(1,0,1)[7] model is shown above. The historical sales data are highly volatile with irregular demand spikes, likely influenced by external events or non-seasonal factors. In contrast, the forecast presents a smoother trajectory, successfully capturing the underlying weekly seasonality and general trend. The confidence intervals remain wide, reflecting the model's uncertainty in predicting extreme fluctuations. While the model does not replicate sudden demand surges, it provides a stable and interpretable forecast of average expected demand—valuable for strategic planning. Given its strong performance metrics and ability to incorporate seasonal patterns, this model was selected as the most balanced option.

3.4 Market Visibility

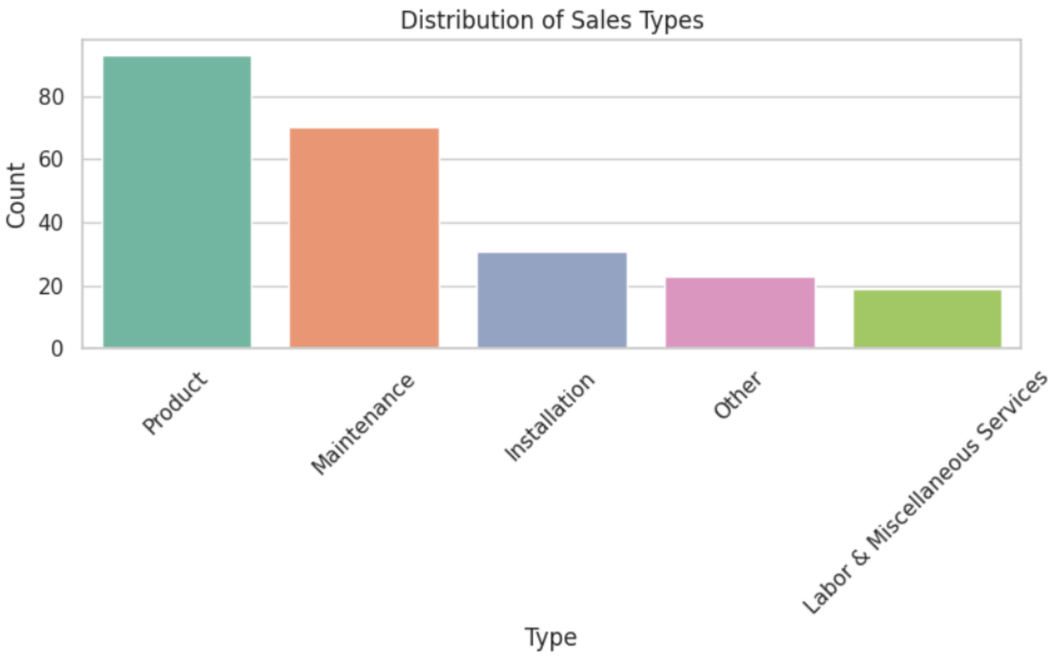

Figure 12: Distribution of Sales Type Graph

The analysis of the sales data reveals several important trends regarding the company's market presence. The below Distribution of Sales Type chart shows that the majority of sales are concentrated in the "Product" and "Maintenance" categories, with "Product" sales leading by a significant margin. "Installation," "Other," and "Labor & Miscellaneous Services" represent much smaller portions of the overall sales mix. This suggests that the company is primarily recognized for its products, while its service offerings have less market traction.

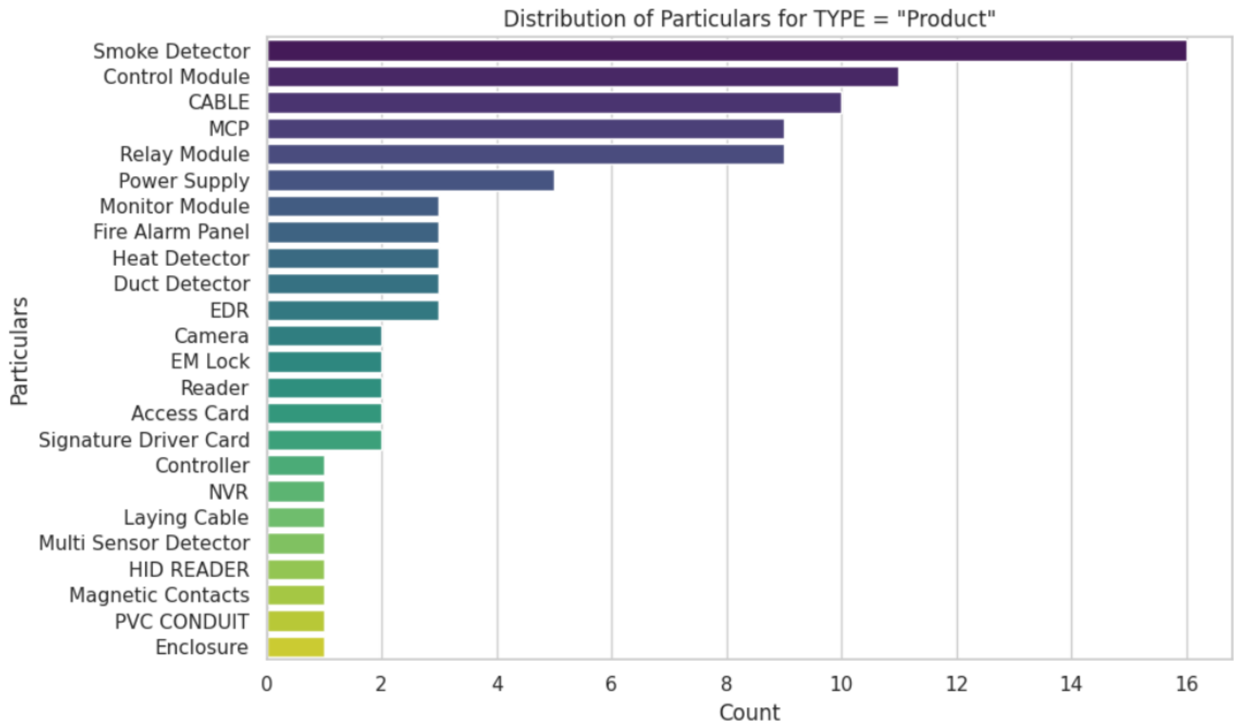

Figure 13: Distribution of Particulars for TYPE = "Product" Graph

Delving deeper into the "Product" category, the second chart of Distribution of Particulars for TYPE= ‘Product’ highlights that sales are heavily skewed toward a few specific items. "Smoke Detector," "Control Module," "CABLE," "MCP," and "Relay Module" dominate the product sales, while a long tail of other products sees much lower sales volumes. This concentration indicates that while the company has a broad product portfolio, only a handful of products are driving visibility and revenue. The limited performance of other products and service categories points to a lack of broad market awareness and penetration across the full range of offerings.

4 Interpretation of Results and Recommendations

4.1 Customer Base Understanding

Interpretation of Results

The application of RFM (Recency, Frequency, Monetary) analysis and K-Means clustering has revealed critical insights into VP Fire and Security System’s customer base. Out of the 20 clients analyzed, 50% fall under the Mid-Value segment, 7 are High-Value VIP clients, and 3 are Low-Value customers. Further, cluster analysis validated and refined these segments, clearly identifying a Top VIP, a Loyal cluster, and a Churn-risk group. The segmentation highlights that while the company has a strong core of loyal clients, it lacks effective engagement strategies for at-risk and dormant high-value accounts. The lack of a granular customer understanding has hindered personalized targeting, limiting sales opportunities and loyalty development across segments.

Actionable Recommendations (SMART Framework)

1. **Develop Targeted Campaigns for Each Segment**
    - **Specific**: Create personalized email and outreach campaigns for VIP, Loyal, and At-Risk clients.
    - **Measurable**: Track open rates, click-throughs, and conversion for each segment.
    - **Achievable**: Use existing CRM tools and RFM segmentation data.
    - **Relevant**: Aligns with business need to improve engagement.
    - **Time-bound**: Launch initial campaigns within 4 weeks.
2. **Initiate Win-Back Programs for Dormant Clients**
    - Target the "At Risk" and "Can't Lose" clients with reactivation offers or personal follow-ups.
    - Time-bound rollout within 30 days and reassess impact after 2 months.
3. **Assign Relationship Managers to High-Value Clients**
    - Prioritize clients like *Honeywell Automation India Ltd.* with a perfect RFM score of 12.
    - Ensure monthly check-ins and custom offers to boost retention and up-selling.
4. **Refine Segmentation Using Clustering Insights**
    - Integrate K-Means cluster labels into CRM system for more dynamic targeting.
    - Re-cluster quarterly to adapt to changing customer behaviours.
5. **Adopt Personalized Marketing Automation**
    - Automate communication flows for each segment using RFM scores and cluster data.
    - Track engagement over the next 90 days for iterative improvement.

Implementation & Impact

Implementing these recommendations will enable VP Fire and Security System to transition from a one-size-fits-all marketing model to a segmented and personalized approach. This will directly enhance customer retention, reactivation, and satisfaction. In the short term, win-back campaigns can recover dormant revenue, while in the long term, sustained relationship management with VIP and Loyal clients will strengthen recurring revenue and brand trust. Overall, improved customer understanding will empower the company to deliver targeted value, enhance loyalty, and unlock missed sales opportunities.

4.2 Forecasting Seasonal Demand

Interpretation of Results

The analysis of daily sales data using time series decomposition highlighted three key components: trend, weekly seasonality, and residual noise. A clear weekly cycle was evident, with autocorrelation at lag 7 validating the presence of consistent weekly demand patterns. The ADF test confirmed the stationarity of the dataset, allowing for effective ARIMA-based modelling.

Among various ARIMA and SARIMA configurations, the SARIMA(1,1,2)(1,0,1)[7] model delivered the best overall performance with the lowest AIC (520.94), MAE (113,641.08), and WAPE (101.82%). While the model couldn't predict irregular demand spikes, it effectively captured general seasonal trends. This provides a stable and realistic forecast, crucial for managing manpower and inventory during high-demand festive periods such as November.

Actionable Recommendations (SMART Framework):

1. **Implement SARIMA-Based Demand Forecasting**
    - **Specific**: Use SARIMA(1,1,2)(1,0,1)[7] to generate rolling 3-month forecasts.
    - **Measurable**: Compare forecast vs. actual demand weekly to track prediction accuracy.
    - **Achievable**: Model has already been tested and validated on historical data.
    - **Relevant**: Directly addresses forecasting weaknesses during seasonal peaks.
    - **Time-bound**: Automate forecasts on a monthly basis starting from next quarter.
2. **Align Inventory Planning with Forecasts**
    - Use weekly demand predictions to pre-stock critical inventory 2–3 weeks in advance of known peaks (e.g., festivals in November).
    - Begin implementation with upcoming quarterly cycle and adjust based on stock-out data.
3. **Adjust Workforce Allocation Based on Predicted Peaks**
    - Forecasted demand can guide advance scheduling of additional temporary or part-time staff during predicted high-demand weeks.

- Pilot this strategy during the next festive season and measure reduction in service delays or missed sales.

<u>Implementation & Impact</u>

Implementing a SARIMA-based forecasting system will significantly enhance VP Fire and Security System’s ability to prepare for seasonal demand fluctuations. Short-term benefits include improved inventory availability and reduced manpower shortages during peak seasons like November. In the long term, consistent forecast-based planning will minimize lost sales opportunities, increase customer satisfaction, and reduce operational bottlenecks. The company will also be better positioned to manage unpredictable external events by continuously refining its forecasting models.

4.3 Market Visibility

- **Broaden Marketing Focus**: Shift marketing efforts beyond the company's top-selling products to promote a wider range of offerings, especially in underserved segments like hotels and hospitals.
- **Promote Underperforming Categories**: Actively market lesser-known services and products in categories such as *Installation*, *Other*, and *Labor & Miscellaneous Services* to improve recognition and demand.
- **Product-Specific Campaigns**: Launch targeted promotional campaigns for underrepresented products within the "Product" category to increase market awareness and boost category-level performance.
- **Product-Specific Campaigns**: Launch targeted promotional campaigns for underrepresented products within the "Product" category to increase market awareness and boost category-level performance.
- **Cross-Promotion Strategies**: Utilize the market traction of best-selling items (e.g., Smoke Detectors and Control Modules) to cross-sell related products and bundled solutions, expanding customer engagement across product lines.
- **Leverage Digital Marketing**: Invest in digital marketing strategies such as SEO, paid ads, email campaigns, and social media to build brand recognition, especially among decision-makers in target industries.