Journal of Advances in Developmental Research (IJAIDR)
E-ISSN: 0976-4844 ● Website: www.ijaidr.com ● Email: editor@ijaidr.com

Predictive Model for Precise Delivery Date

Arulmozhi Kasthurirengan

arulmozhi.j@gmail.com

Abstract:
This paper addresses the critical issue of inconsistent and unclear delivery messaging within the e-commerce shopping funnel, identified upon joining the Delivery and Fulfillment Channel of the Supply Chain Network in a leading organization. The lack of clarity in delivery promises has been recognized as a significant contributor to cart abandonment and increased customer service inquiries. Delivery logistics inherently involve a complex network of stakeholders—including carriers, manufacturers, distributors, and end customers—each introducing potential variability to fulfillment timelines. Both external factors, such as weather disruptions, holidays, and weekends, and internal factors, including order processing inefficiencies, tracking inaccuracies, communication breakdowns, and transportation delays, further exacerbate this challenge. This study explores a structured approach to modeling and implementing Precise Delivery Date (PDD) systems aimed at enhancing delivery predictability, improving customer trust, and reducing operational friction across the supply chain.

Keywords: Predictive Algorithm, On Time Accuracy, Estimated Variance, Post-Purchase Experience, Machine Learning, Artificial Intelligence, Key Performing Indicators.

INTRODUCTION

As cited in Shipper HQ, the Importance of Displaying Estimated Delivery Dates to the Customers at the Checkout are: Even if there are any delays in delivery, it is still important to give customers a clear picture of the delivery process of their orders at the checkout.

Convenience and Predictability - It is about going the extra mile and showing the customers our willingness to fit their busy schedule. Imagine the following scenario, a customer goes on a holiday and needs new equipment to be shipped before the weekend starts. It is crucial to display the most accurate delivery dates to help your customer choose the best shipping method. Also, this option is very convenient when the holiday season approaches, during Christmas or Black Friday when shipping needs to be extra predictable.

Customer Trust and Satisfaction - Build trust with our customers by being a reliable and trustworthy retailer. Always we have to display the most accurate estimated delivery dates and make sure we meet them. At the end of the day, a satisfied customer is also a loyal customer.

Security and Efficiency - Delivery dates add an extra layer of security to your customers. With this feature, a customer can indicate when he is available to sign the order directly from the delivery man. By scheduling the delivery, a distributor also avoids the option to leave the parcel at the doorstep or at the neighbors', which might be less secure. The delivery dates feature also helps with the smooth process of logistics and prevents time-wasting for both the customer and shipping carrier.

Strict Delivery Time Frame - Customers will appreciate the punctuality of the delivery.

Hence, it was believed that if we build a way to more accurately predict the true delivery timeline for customer orders and message this more consistently in Product Detailed Page (PDP), Bag/Cart & Check out pages, this will improve both final product selection and fulfillment method. As a result, this will lead to higher turnover and less calls to customer service agents due to a clear idea of when to expect their orders to arrive.

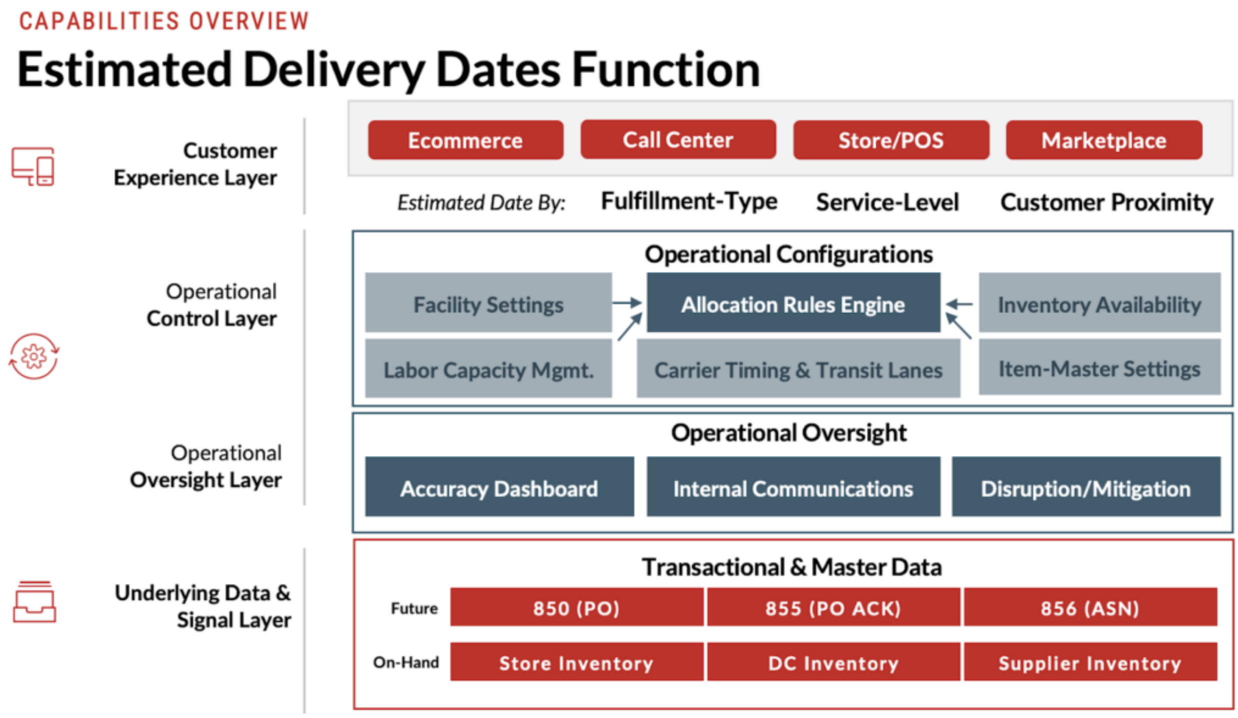

Fig 1 : Functioning of Delivery Date

ACTION

In order to be able to predict more accurate delivery days for customer orders, **Predictive Algorithm** to build a data science prediction model which can use real fulfillment data such as Shipping and transit time as inputs to estimate the number of delivery days to the customers. Apart from these input variables, a configurable buffer by Brand, Fulfillment Type, Location and Ship Method level to achieve target accuracy by optimizing model estimates for transit time. This buffer can be adjusted for the orders fulfilled by Distribution Centers (DC)/Warehouses, and Vendors directly.

During the POC (Proof of Concept) stage of this model, **Process Flow** was created to have Data Ingestion from Oracle tables, Data Cleaning to remove anomalies, Model execution to predict Ship Days, Model File Creation to add other required details such as transit days and Generate **KPIs** (Key Performance Indicators). As part of the Validation Steps between Predictions and Actuals, have come up with the logic to calculate the delivery days based on the data from previous 5 weeks for predictions, to calculate the delivery days based on the data from the last 1 week for Actuals and to Run the KPI with Predictions and Actuals as inputs by calculating the accuracies based on the formulate for each delivery type with buffer and without buffer.

Also, it was identified that we need an additional buffer for Buy Online Ship to Store (BOSS) orders at location level to account for average processing time to handle the packages arriving at the store, bring from docs to desk, scan and place in store location and then make it ready for customer pickup. Then, Primary Model KPI Metrics was built to measure Model's Performance in terms of **On Time Accuracy and Estimated Variance.** After completing the KPI Metrics, it was realized that the **dashboard** would help our business stakeholders to visualize the KPI in graphical format.

Moreover, some changes were proposed to enhance the current **End-to-End Post-Purchase Experience** for Experimentation & Scale by communicating Precise Delivery Date in Order Confirmation Email, Order Shipped Email, Order Delayed Email and Order Delivered Email. Then to increase the Model's On Time Accuracy and to decrease the Estimated Variance between Predicted Vs Actual delivery dates, I worked with our development team to generate a better model using **Machine Learning Algorithm**. an **E2E Test Plan**

was created to test Brands, Pre-Transaction Pages including PDP, Bag, Checkout, Order History, Order Confirm/Ship Confirm Emails, Order Methods such as Store, Warehouse and Vendor and Standard, Express, Premium, Same Day and No Hurry Ship Methods.
It was suggested the capability of business stakeholders submit a request to **Operations and Support groups** by specifying the control settings to be changed. worked with Operations teams to prioritize the request based on the typical support SLAs (Service Level Agreement) based on Severity and Priority on the request. Also, proposed an approach to expose REST API services to make backend data changes on application's database and memory store. Since this procedure has manual intervention, it was realized that there can be more probabilities for human errors. So, it was decided to automate this process later.

Then, the Finance group arrived a **Cost Mitigation Plan** to keep upgrade cost as low as possible without compromising customer experience by training the model for higher accuracy rate for holiday and seasonality as part of Pre-Experiment phase. Adjusted buffer and turn kill switch off by Brand, Fulfillment Type, Location and Ship Method level. Incorporated additional data points such as Carrier pick & wait time and passed Precise Delivery Date downstream to optimize shipping & fulfillment logic accordingly.

Also, a **Contingency Plan** was created to detect and handle Anomalies such as Seasonality/Peak Traffic, Global/National Pandemic, Regional Supply Chain Disruptions, and Demand surge due to unforeseen events and developments by training the model on a daily basis to adjust the time to ship automatically.

DEPENDENCIES, CHALLENGES & RISK

Worked with cross-functional teams to have an alignment between **Calendar and Business Days** as part of the delivery days calculation as weekend deliveries were not happening due to contract limitations with carriers. Also worked with the delivery partners to reduce the 1-day gap between Displayed Delivery Date and Actual Arrival. Coordinated with carriers to fetch the real time feed from carriers. Also proposed probabilistic PDD durations via Conditional PDD model to provide the possible delivery date ranges with the model.

MODEL ENHANCEMENTS

As part of **DC & Store ML Model,** the Regression Classification is finalized, Data Sampling/ML Algorithm selection, Model Testing and Tuning, Passive testing in prod, Branch off models based on insights as feasible, Prod Experiment with 15%-25% Control Group.
Also, proposed **MLOps Pipeline** to process design, choose pipeline tool choice, build a pipeline, Integrated with MLOps pipeline based on platform team's availability, Dashboarding using DataStudio/Grafana, Moderate PDD Dashboard Insights and add AI/ML Insights.

FUTURE WORK

Created Two years Roadmap to add more value to the current model that includes the **additional factors** such as Backlog Time, Delivery/Buffer days in Decimal, Automate the process to include new locations, Extending the current prediction logic to transit day estimation. Also, there is a plan to account for Carrier Holidays and calculate dynamic transit time by consolidating the transit days by carrier integration, to serve Real-time predictions via Rest API and Conditional PDD from Machine Learning Model and to create a **Self-Service Portal** for business users to configure buffer and threshold.

CONCLUSION

There are so many benefits of using the prediction model such as Dynamic detection of patterns and rate of change, Responsive to trends in immediate dataset, Continuous learning and improvement, Flexibility offered by buffer. As a result of this model implementation, our **Add To Bag (ATB), Bag to Order Rate (BTO)**

increased by 0.7% and the customer calls are reduced by -35%. Also, this increased the sales, and reduced the cost of upgrades and delivery,
The **KPI Dashboard** helped us to analyze the trend by having **Daily & Weekly Insights** on aggregated stats between Predicted and Actual Delivery Days including Ship Days and Transit Days across all the Brands, Fulfillment Types, Locations and Ship Methods

REFERENCES:

1. Shipper HQ (2022): https://blog.shipperhq.com/2024/09/avoid-these-common-mistakes-when-calculating-delivery-date-estimates
2. Fluent Commerce (2023): https://www.insureshield.com/us/en/resources/insights/understanding-shipping-and-estimated-delivery-dates.html
3. Sendflex (2023): https://www.sendflex.com/resources/articles/stop-guessing-use-machine-learning-to-improve-delivery-predictions#:~:text=EDDs%20provide%20customers%20with%20a%20specific%20date,destination%2C%20and%20conditions%20like%20weather%20and%20traffic.
4. Calculrates: https://calcurates.com/the-importance-of-showing-delivery-dates
5. Investopedia: https://www.investopedia.com/terms/d/deliverydate.asp