

A.S.T.R.O. (Advanced Supply and Trade Resource Optimisation)

Project Group 03

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INTRODUCTION

- **Introduction**
 - ASTRO helps small vendors with purchasing and delivery challenges.
 - Vendors struggle with high costs, poor supply chains, and low bargaining power.
 - Key features:
 - Order aggregation for bulk discounts.
 - Demand forecasting for better planning.
 - Optimized supplier selection for cost savings.
 - Uses Environment Adaptive Genetic Algorithm for efficient deliveries.
 - Compares supplier selection methods for best deals.
 - Provides a scalable, cost-effective supply chain solution.
 - Boosts competitiveness and sustainability for vendors.

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PROBLEM STATEMENT

- Design a collaborative platform which
 - Enables multiple vendors to aggregate orders, facilitating bulk purchasing and cost savings.
 - Demand forecasting to predict product needs accurately
 - Implement route optimization techniques to establish an efficient delivery network.
- This approach aims to enhance supply chain efficiency, reduce operational costs, and strengthen the market position of small-scale vendors.

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OBJECTIVES

- **Objectives of the Project**
 - Order Aggregation : Allow vendors to combine purchases for bulk discounts.
 - Demand Forecasting : Predict demand to optimize purchasing.
 - Logistics Optimization : Reduce delivery costs using Green Routing Optimization.
 - Supplier Selection : Identify cost-effective and reliable suppliers.
 - Vendor Competitiveness : Help small vendors compete with large retail chains.

- **Importance and relevance of the project**

ASTRO helps small-scale vendors reduce costs, improve supply chain efficiency, and compete with large retail chains. By enabling order aggregation, demand forecasting, and optimized logistics, the platform ensures better pricing, faster deliveries, and smarter purchasing decisions. It promotes cost-effectiveness, scalability, and sustainability, making it highly relevant in today's competitive market.

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PROJECT SCOPE

- **Project Scope: Boundaries and Focus**
 - ASTRO is designed to enhance procurement and logistics for small-scale vendors by leveraging order aggregation, demand forecasting, and supplier selection optimization. The platform aims to reduce procurement costs, streamline deliveries, and improve vendor-supplier collaboration, making supply chain management more efficient, data-driven, and cost-effective.
- **What is Covered**
 - **Order Aggregation** : Enables vendors to combine orders for bulk purchase discounts.
 - **Demand Forecasting** : Utilizes data-driven analytics to predict demand and optimize procurement.
 - **Logistics Optimization** : Implements Green Routing Optimization for cost-efficient and timely deliveries.
 - **Supplier Coordination** : Streamlines vendor-supplier interactions for efficient order processing
- **What is Excluded**
 - **Inventory Management** : Does not handle warehouse stock tracking or inventory control.
 - **Retail Consumer Sales** : Exclusively focuses on vendor-supplier transactions, not direct customer sales.
 - **Financial Transactions** : Does not process payments, financing, or lending services.

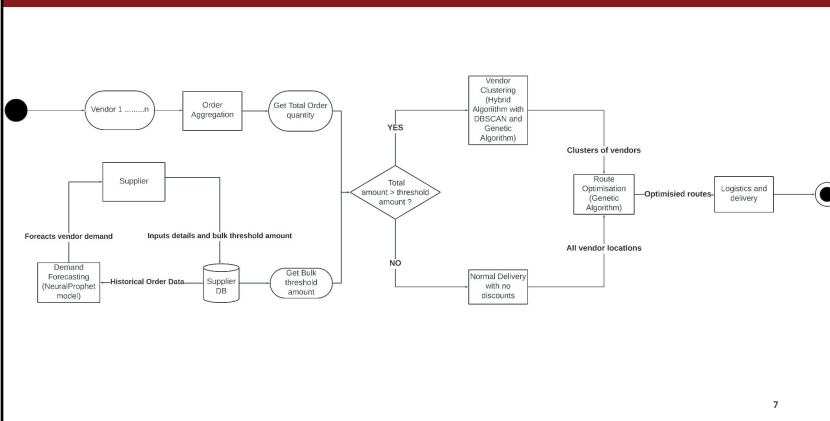
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METHODOLOGY

- **Tools & Technologies**
 - **Frontend** : React JS
 - **Backend** : FastAPI Python
 - **Programming Languages** : Python and TypeScript
 - **Database**: Firebase Firestore
 - **APIs & Integrations** : Ola Maps
- **Dataset**
 - Store Item Demand Forecasting Challenge - Kaggle Dataset ([Kaggle Link](#))
 - Random Google Maps Business Locations - South India
- **Algorithms Used**
 - **Route Optimization** : Genetic Algorithm
 - **Order Aggregation** : DBSCAN along with Genetic Algorithm
 - **Demand Forecasting** : NeuralProphet ([Link](#))

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SYSTEM DESIGN



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SYSTEM DESIGN

- **Data Collection & Storage**
 - Orders are stored in Google Firestore with details like supplier ID, vendor location, order quantity, and status.
 - Suppliers set a Minimum Order Quantity (MOQ) for aggregation.
- **Order Aggregation using DBSCAN along with Genetic Algorithm**
 - **Location-Based Clustering**: Orders from vendors are clustered using DBSCAN based on real-world (Haversine) distances.
 - **Dynamic Parameter Tuning**: A Genetic Algorithm optimizes DBSCAN's parameters (eps, min_samples) for better clustering accuracy.
 - **MOQ Validation & Fallback**: Clusters are accepted only if they meet Minimum Order Quantity (MOQ); otherwise, orders remain pending. Default DBSCAN is used if order volume is low.

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SYSTEM DESIGN

- **Route Optimization using EAGA:**

- Aggregated orders require efficient delivery routes.
- EAGA and EAACO algorithm compared for implementing which are modifications made to GA and ACO to use a custom cost function.
- The cost function integrates distance, weather, elevation, and fuel costs with weighted penalties dynamically based on dataset size
- Our Total Cost (TC) function combines four critical factors for optimal route selection

$$TC = (Distance\ Weight \times Distance\ Cost) + (Weather\ Weight \times Weather\ Cost) + (Elevation\ Weight \times Elevation\ Cost) + (Fuel\ Weight \times Fuel\ Cost)$$

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SYSTEM DESIGN

- **Cost Function Components**

$$TC = (Distance\ Weight \times Distance\ Cost) + (Weather\ Weight \times Weather\ Cost) + (Elevation\ Weight \times Elevation\ Cost) + (Fuel\ Weight \times Fuel\ Cost)$$

- **1. Weather Cost Components**

- Temperature Penalty: Applies when temperature exceeds 30°C:

$$Cost = 0.05 \times (Avg\ Temp - 25)^2$$

- Precipitation Penalty: Scales with rainfall intensity:

$$Cost = 0.2 \times Average\ Precipitation$$

- Wind Penalty: Triggers for winds >10 m/s:

$$Cost = 0.1 \times (Avg\ Wind\ Speed - 5)^2$$

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SYSTEM DESIGN

- **2. Elevation Cost**

- Accounts for terrain difficulty:

$$Cost = 0.005 \times (Elevation\ Change / 100)^2$$

- **3. Fuel Cost Breakdown**

- Temperature Impact: +1% consumption per °C above 30°C
- Wind Impact: +2% consumption per m/s above 5 m/s
- Elevation Impact:
 - Uphill: +0.05% per meter climbed
 - Downhill: -0.03% per meter descende

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SYSTEM DESIGN

- **Demand Forecasting using NeuralProphet :**

- Historical order data is analyzed using NeuralProphet (an advanced time-series forecasting model).
- Forecasts future demand patterns, helping suppliers plan inventory and pricing.
- Helps detect seasonal demand fluctuations

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IMPLEMENTATION

- **Order Aggregation using DBSCAN along with Genetic Algorithm**
 - **DBSCAN (Density-Based Spatial Clustering of Applications with Noise)**
 - Unsupervised clustering algorithm.
 - Groups dense points; marks low-density points as outliers.
 - No need to predefine the number of clusters (unlike k-means).
 - **Why Use DBSCAN Instead of Other Algorithms?**
 - Better for Geospatial Clustering: Excels at location-based clustering.
 - Automatic Cluster Discovery: No need to predefine the number of clusters.
 - Handles Noise & Outliers: Avoids forcing outliers into clusters.
 - Flexible Shapes: Detects irregular cluster shapes (unlike k-means).
 - **Why Use Genetic Algorithm**
 - Traditional DBSCAN requires fixed ϵ s and $\min_samples$, which don't adapt to changing vendor order patterns.
 - To overcome this, we combine DBSCAN with a Genetic Algorithm (GA) that automatically optimizes these parameters for each dataset.

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IMPLEMENTATION

- **Order Aggregation using GADBSCAN Clustering**
 - **How DBSCAN along with GENETIC ALGORITHM Works?**
 - Input: Order coordinates (latitude, longitude), and quantities.
 - Distance Calculation: Compute Haversine distance matrix between all vendor locations.
 - Optimization: Run Genetic Algorithm to find optimal ϵ s and $\min_samples$ for DBSCAN.
 - DBSCAN Clustering:
 - Run DBSCAN using the GA-tuned parameters.
 - Identify clusters of geographically close orders.
 - MOQ Validation:
 - Each cluster is accepted only if it meets MOQ (plus buffer).
 - Outliers or low-quantity clusters are kept pending.
 - **Advantages Over Traditional DBSCAN**
 - Dynamic Parameter Tuning: Automatically finds the best ϵ s and $\min_samples$ using Genetic Algorithm.
 - MOQ-Aware Clustering: Ensures clusters are only accepted if they meet Minimum Order Quantity.
 - Adaptive to Varying Data Volumes: Switches between optimized and default DBSCAN based on order count.
 - Real-World Distance Support: Uses Haversine distance for accurate location-based clustering.
 - Robust Outlier Handling: Effectively filters noise and avoids misgrouping of outliers.

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IMPLEMENTATION

- **Route Optimization using Environment Adaptive Ant Colony Optimization (EAACO) :**
 - **Why Use EAACO?**
 - Context-Aware Routing: Dynamically adjusts to weather, traffic, and terrain in real-time
 - Multi-Objective Optimization: Balances distance, time, fuel efficiency, and operational constraints
 - Enhanced Convergence: Adaptive pheromone updating accelerates optimal solution discovery
 - **How EAACO Works?**
 - Dynamic Parameter Adjustment
 - Pheromone sensitivity (α) adapts to route complexity
 - Environmental heuristic (β) auto-tunes for weather/elevation impacts
 - Smart evaporation rate prevents premature convergence
 - Hybrid Cost Evaluation
 - Distance metrics
 - Real-time weather penalties
 - Terrain difficulty scores

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IMPLEMENTATION

- **Route Optimization using Environment Adaptive Ant Colony Optimization (EAACO) :**
 - **How EAACO Works?**
 - Route Construction:
 - Ants are placed at random locations.
 - Each ant builds a route probabilistically based on pheromone trails (past successful paths) and the cost function
 - **EAACO in this Project**
 - Extracts Order Locations (latitude & longitude).
 - Constructs Distance Matrix using Ola Maps API
 - Optimizes Fuel Cost by considering cost per liter.
 - Builds Routes using probability-based selection.
 - Applies 2-Opt Local Search for further route optimization.
 - Stops Early if no improvement is detected to save computation time.

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IMPLEMENTATION

- **Route Optimization using Environment Adaptive Genetic Algorithm (EAGA):**
 - The Environment Adaptive Genetic Algorithm (EAGA), a specialized GA variant, is designed to dynamically adjust to changing environmental conditions in logistics routes.
 - More efficient than traditional routing by exploring multiple possibilities in parallel.
 - **Why Use Genetic Algorithms?**
 - Efficient Optimization: Faster than brute-force search.
 - Scalable: Works with large datasets.
 - Avoids Local Minima: Prevents getting stuck in suboptimal solutions.
 - **How It Works:**
 - Key Components:
 - Population: Set of possible routes.
 - Selection: Picks best routes for reproduction.
 - Crossover: Combines parent routes.
 - Mutation: Introduces random changes for diversity.

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IMPLEMENTATION

- **Route Optimization using Environment Adaptive Genetic Algorithm (EAGA):**
 - **How It Works:**
 - Initialize: Generate routes (Greedy Nearest Neighbor, 2-Opt).
 - Evaluate: Compute distance, favor shorter routes.
 - Select: Pick best routes (Tournament Selection).
 - Crossover & Mutation: Mix routes (OX, ERX) + random changes.
 - Refine: Apply 2-Opt for optimization.
 - Converge: Stop when no further improvement.
 - **EAGA in this Project**
 - Extracts order locations (latitude & longitude).
 - Computes Distance Matrix using Ola Maps API
 - Runs GA with adaptive mutation rates for optimization.
 - Applies 2-Opt Local Search for final refinement.
 - Selects the best route with minimal delivery time & cost.

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CHALLENGES

- **Order Aggregation Challenges**
 - **Issue:**
 - Clustering vendor orders using DBSCAN required careful tuning of parameters like eps (neighborhood radius) and min_samples.
 - Additionally, clustering had to satisfy Minimum Order Quantity (MOQ) constraints while reducing outliers.
 - **Solution:**
 - Replaced manual tuning with Genetic Algorithm (GA) to dynamically optimize eps and min_samples for DBSCAN.
 - GA uses a fitness function that maximizes valid clusters while minimizing noise.
 - Integrated MOQ checks post-clustering to ensure only qualifying clusters are confirmed for aggregation.
 - Enhanced outlier handling by isolating orders that don't meet MOQ, marking them as pending for future rounds.

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CHALLENGES

- **Route Optimization Challenges**
 - **Issue:**
 - Genetic Algorithm required careful tuning of parameters such as population size, mutation rate, and crossover strategy to effectively handle real-world constraints like traffic patterns, delivery time windows, and vendor/supplier availability.
 - **Solution:**
 - Dynamic Parameter Scaling automatically adjusts based on problem size (number of vendors v)
 - Ensured diversity in the population using mutation and elitism to avoid premature convergence.

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CHALLENGES

- **Demand Forecasting Challenges**
 - **Issue:**
 - Forecasting demand using NeuralProphet required high-quality historical data.
 - **Solution:**
 - Applied data cleaning techniques (removing inconsistencies, handling missing values).
 - Used hyperparameter tuning to improve forecast accuracy.

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PERFORMANCE ANALYSIS

- **Vendor Clustering and Order Aggregation**
 - Comparisons were done between Agglomerative Clustering , K-means ,DBSCAN and GA-DBSCAN
 - Synthetic datasets were generated with latitudes 8°–18° and longitudes 72°–82° to simulate real-world distributions.
 - Each order quantity was randomized between 50% and 150% of the MOQ; MOQ was set to 100 units with a 20% buffer.
 - Valid cluster quantities ranged between 100 and 120 units.
 - Experiments were run on datasets with 25, 50, 100, 150, 200, 300, and 350 orders.
 - Evaluation metrics included execution time, valid clusters, leftover orders, and silhouette scores.
 - Silhouette score measured clustering quality from -1 (poor) to +1 (excellent).

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PERFORMANCE ANALYSIS

Algorithm	Orders	Time (s)	Clusters	Outliers	Silh. Score
DBSCAN	25	0.002	7	16	0.350
	50	0.002	13	32	0.330
	100	0.003	28	68	0.392
	150	0.004	39	99	0.380
	200	0.005	63	118	0.375
	300	0.009	85	187	0.361
GA-DBSCAN	350	0.010	98	219	0.355
	25	0.020	0	25	N/A
	50	0.025	0	50	N/A
	100	0.025	11	89	0.735
	150	0.030	12	138	0.780
	200	0.036	39	156	0.726
K-means	300	0.048	35	262	0.715
	350	0.055	45	301	0.629
	25	0.030	6	18	0.358
	50	0.004	12	34	0.324
	100	0.004	26	72	0.392
	150	0.005	37	103	0.390
Agglomerative	200	0.032	61	122	0.385
	300	0.007	84	189	0.363
	350	0.008	94	227	0.350
	25	0.002	6	18	0.341
	50	0.002	12	34	0.337
	100	0.002	27	70	0.393
	150	0.004	38	101	0.358
	200	0.005	61	122	0.359
	300	0.007	84	189	0.359
	350	0.009	95	225	0.349

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PERFORMANCE ANALYSIS

- **Vendor Clustering and Order Aggregation**
 - GA-DBSCAN achieved the highest silhouette scores (0.629–0.780) in datasets with 100 orders and above, indicating superior clustering quality.
 - It failed to produce valid clusters for smaller datasets (25 and 50 orders) due to ineffective genetic optimization on limited data.
 - In smaller datasets, DBSCAN, K-means, and Agglomerative Clustering outperformed GA-DBSCAN, with DBSCAN being the fastest.
 - For larger datasets, GA-DBSCAN excelled by adaptively tuning ϵ and min_samples , enhancing clustering accuracy.
 - K-means and Agglomerative methods often resulted in more clusters and leftover orders due to their fixed parameters.
 - Standard DBSCAN, while fast, produced less coherent clusters in larger datasets because of static parameter limitations.
 - Leftover orders occurred when groups failed to meet MOQ or were geographically isolated.
 - Silhouette scores measured cluster quality based on compactness and separation.
 - Results support a hybrid approach: use DBSCAN for smaller datasets and GA-DBSCAN for larger, more complex scenarios.

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PERFORMANCE ANALYSIS

• Route Optimization

- EAGA consistently outperformed EAACO in both travel distance and execution time across all vendor sizes.
- For 20 vendors, EAGA covered 4703.90 km in 20.53 seconds, while EAACO took 23.26 seconds for 5197.54 km.
- With 50 vendors, EAGA optimized the route to 6993.30 km in 60.75 seconds; EAACO covered 8333.63 km in 50.43 seconds.
- For 100 vendors, EAGA achieved 8581.06 km in 142.21 seconds, compared to EAACO's 9648.29 km in 148.69 seconds.
- EAGA's superior performance is attributed to its faster convergence and efficient balance between exploration and exploitation.
- EAACO required more iterations for refinement, leading to longer routes and increased execution times.

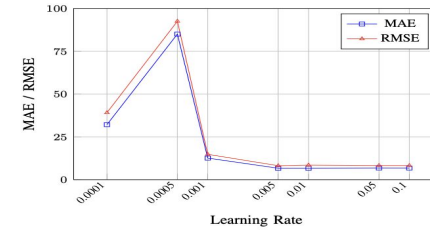
Algorithm	Vendors	Dist. (km)	Cost (Rs.)	Time (s)
EAACO	20	5197.54	29811.51	23.26
	50	8333.63	47618.80	50.43
	100	9648.29	54444.64	148.69
EAGA	20	4703.90	22320.78	20.53
	50	6993.30	33770.55	60.75
	100	8581.06	40956.56	142.21

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PERFORMANCE ANALYSIS

• Demand Forecasting

- The NeuralProphet model was evaluated using the Store Item Demand Forecasting Challenge dataset, which provides historical daily sales data for multiple store-item combinations. For this analysis, we specifically focused on item 1 from the dataset to demonstrate the model's performance on a representative product time series. Performance was assessed using standard error metrics to evaluate forecasting accuracy across different learning rate and training epoch.



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PERFORMANCE ANALYSIS

• Demand Forecasting

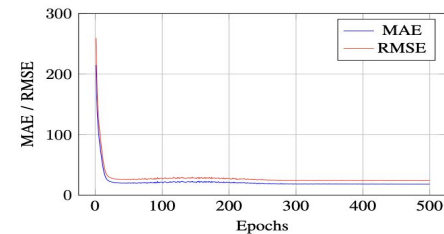
- Figure shows a U-shaped trend in error metrics with respect to learning rate.
- Optimal accuracy is observed between learning rates of 0.005 and 0.01.
- At a very low rate (0.0001), the model converges slowly, resulting in higher errors (MAE = 32.14, RMSE = 39.12).
- At 0.0005, performance drops sharply (MAE = 85.04, RMSE = 92.52), likely due to convergence to a poor local minimum.
- Beyond 0.01, errors stabilize, showing the model's robustness to higher learning rates.
- The best performance is at a learning rate of 0.005, with the lowest MAE (6.69) and RMSE (8.16).

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PERFORMANCE ANALYSIS

• Demand Forecasting

- Figure shows the evolution of MAE and RMSE over training epochs.
- Both metrics drop rapidly in the first 100 epochs, then improve gradually, converging around 400 epochs.
- This reflects typical neural network learning behavior—fast early improvements followed by slower refinements.



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RESULTS AND EVALUATION

• Cost Comparison Analysis :

- To evaluate the collaborative ordering and shared delivery model, route optimization was tested across 50 vendors.
- The analysis compared traditional individual delivery routes with the proposed collaborative approach.
- In the traditional method, five separate routes were planned, often with overlapping paths.
- The collaborative model consolidated all deliveries into a single optimized route.
- This resulted in significant savings in travel distance, cost, and fuel consumption.
- The evaluated delivery network spanned approximately 7,000 km, showcasing the efficiency of route consolidation.

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RESULTS AND EVALUATION

• Cost Comparison Analysis :

- The traditional delivery approach involved separate or small-group delivery routes, leading to route overlap and inefficiencies.
- This method resulted in a total travel distance of 35,606.06 km, costing Rs. 36,929.20, with fuel usage of 1,811.34 L and fuel costs of Rs. 171,135.40.
- The collaborative delivery model, powered by EAGA, consolidated deliveries into a single optimized route.
- This reduced travel distance to 6,993.30 km, cutting total route costs to Rs. 7,254.56, with fuel usage down to 357.43 L and fuel costs at Rs. 33,769.57.
- The approach achieved an 80.4% reduction in travel distance and delivery costs, and an 80.3% fuel savings.

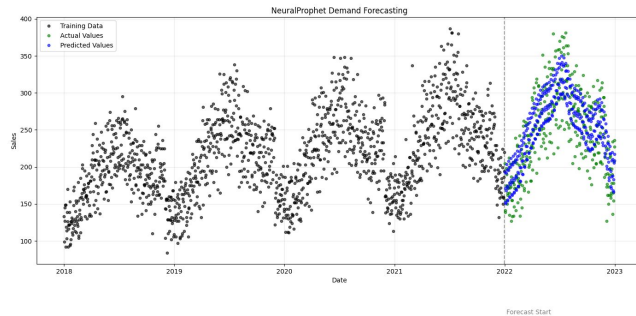
Metric	Trad.	Collab.	Savings
Distance (km)	35,606	6,993	28,613 (80.4%)
Route Cost (Rs.)	36,929	7,255	29,675 (80.4%)
Fuel (L)	1,811	357	1,454 (80.3%)
Fuel Cost (Rs.)	171,135	33,770	137,366 (80.3%)

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RESULTS AND EVALUATION

• Demand Forecasting Capabilities :

- Figure illustrates NeuralProphet's ability to predict future order quantities based on historical data, providing vendors with reliable projections for inventory planning. Supporting this predictive capability

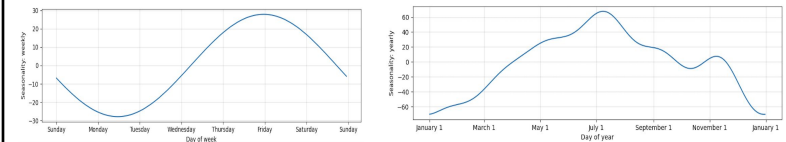


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RESULTS AND EVALUATION

• Demand Forecasting Capabilities :

- The below diagrams demonstrate how the model accurately captures both weekly variations and annual seasonal patterns in vendor ordering behavior. This comprehensive forecasting capability is crucial for vendors and suppliers to anticipate demand fluctuations, optimize inventory management, and plan logistics operations efficiently throughout the year.



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CONCLUSION

- **Summary of the Work Done**
 - ASTRO was developed to enhance procurement and logistics for small-scale vendors.
 - Implemented DBSCAN with Genetic algorithm for order aggregation, Environment Adaptive Genetic Algorithm (EAGA) for route planning, and NeuralProphet for demand forecasting.
- **Limitations of the Project**
 - Accuracy of demand forecasting depends on data availability.
 - Real-world implementation may require additional infrastructure and funding.
 - Inventory management is not covered in the current scope.
- **Suggestions for Future Work**
 - Improve supplier selection with advanced ML models.
 - Integrate real-time tracking for better delivery monitoring.
 - Expand dataset coverage to improve forecasting accuracy.

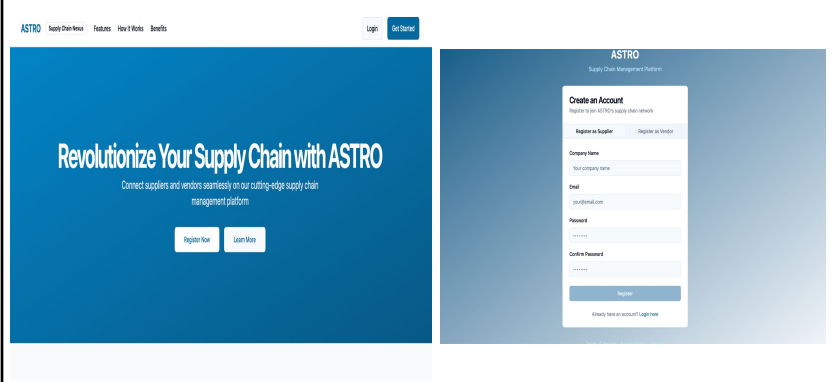
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SOCIETAL RELEVANCE

- **Empowers Small Vendors:**
 - Enables small businesses to collaborate, meet MOQs, and gain access to bulk pricing.
- **Promotes Collaborative Commerce:**
 - Shifts from competitive to cooperative ordering, building local trust networks.
- **Optimizes Deliveries for Sustainability:**
 - Uses smart route planning via EAGA to reduce fuel usage and emissions, directly contributing to SDG 12: Responsible Consumption and Production through more efficient logistics.
- **Boosts Local Economies:**
 - Minimizes procurement and logistics costs, improves vendor profitability, and strengthens local supply chains—driving inclusive economic growth, innovation, and entrepreneurship, which are core aims of SDG 8.
- **Encourages Data-Driven Decisions:**
 - Demand forecasting using NeuralProphet ensures vendors make informed choices, reducing overstock and resource waste—addressing the goals of SDG 12 by promoting sustainable production patterns.
- **Promotes Sustainable Supply Chains:**
 - Aggregated orders and shared delivery systems reduce packaging, transportation redundancy, and carbon footprint, aligning with the vision of SDG 12 for responsible and sustainable consumption.

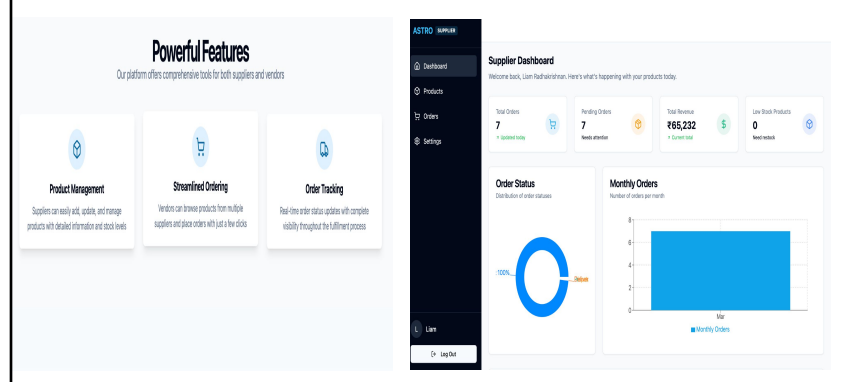
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SCREENSHOTS



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SCREENSHOTS



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SCREENSHOTS

ASTRO HARPER

Dashboard

Products

Orders

Settings

Logout

Products

Manage your product inventory

+ Add Product

Product Inventory

You have 20 products in your inventory

Search products...

Name	Category	Price	Inventory	Min. Order Qty	Status	Actions
Snap	Household Items	₹103.00	1000	80	In Stock	...
Handwash	Hygiene Products	₹123.84	976	100	In Stock	...
Toothpaste	Cleaning Supplies	₹188.27	531	177	In Stock	...
Shampoo	Hygiene Products	₹171.6	663	221	In Stock	...
Conditioner	Laundry Care	₹195.23	642	214	In Stock	...
Detergent Powder	Hygiene Products	₹140.17	884	221	In Stock	...
Toothbrush	Cleaning Supplies	₹143.92	549	163	In Stock	...

Orders

Manage orders from your vendors

Order Management

You have 1 orders in order

Search orders...

All Orders

Order ID	Product	Quantity	Total	Status	Date	Actions
KHSO-2275AC3E1P	Snap	80	₹103.072	In Progress	01/10/2025	...
KHSO-2275AC3E1P	Snap	30	₹103.074	In Progress	01/10/2025	...
KHSO-3A10AC3E2D	Snap	80	₹103.074	In Progress	01/10/2025	...
KHSO-4F1E8B9F67	Snap	30	₹103.074	In Progress	01/10/2025	...
KHSO-4F1E8B9F67	Snap	100	₹103.088	In Progress	01/10/2025	...
KHSO-0E103C3B1F34	Snap	80	₹103.084	In Progress	01/10/2025	...
KHSO-4F055AC3E07D	Snap	40	₹103.032	In Progress	01/10/2025	...

SCREENSHOTS

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KHSO-3A10AC3E2D	Snap	80	₹103.074	In Progress	01/10/2025	...
KHSO-4F1E8B9F67	Snap	30	₹103.074	In Progress	01/10/2025	...
KHSO-4F1E8B9F67	Snap	100	₹103.088	In Progress	01/10/2025	...
KHSO-0E103C3B1F34	Snap	80	₹103.084	In Progress	01/10/2025	...
KHSO-4F055AC3E07D	Snap	40	₹103.032	In Progress	01/10/2025	...

Settings

Manage your account and preferences

Account

Notifications

Security

Account Information

Update your account details and preferences

First Name

Last Name

Phone

Email

Shop Name

Role

Address

Building/Street No.

Post/Street

City

State

Pin Code

REFERENCES

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THANK YOU