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

Project Group 03

Amel Chandra (U2109009)
Bharath S (U2109018)
Joepaul Vilsan (U2109033)
Shane George Salphie (U2109063)

Under the Guidance of

Dr. Nikhila T. Bhuvan,
Assosciate Professor,
Department of CSBS

RSET
RAJAGIRI SCHOOL OF ENGINEERING & TECHNOLOGY (AUTONOMOUS)

Dept. of Computer Science and Business Systems,
RSET

CONTENTS

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.

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.

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.
- **Societal Relevance**
  - Optimizes Deliveries : EAGA-based route planning reduces fuel and emissions, supporting SDG 12 through efficient logistics.
  - Boosts Local Economies : Lowers procurement costs, raises vendor profits, and fosters inclusive growth in line with SDG 8.
  - Data-Driven Decisions : NeuralProphet forecasting reduces overstock and waste, promoting sustainable practices per SDG 12.
  - Sustainable Supply Chains : Shared orders and routes cut packaging waste and transport redundancy, advancing SDG 12 goals.

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.

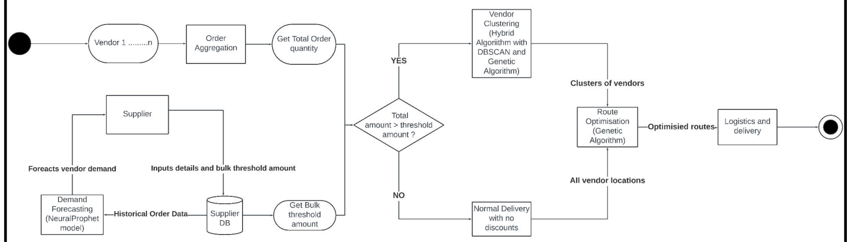
TOOLS & TECHNOLOGIES

- **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)

SYSTEM DESIGN



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.

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
- **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

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 eps 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.

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 eps 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 eps 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.

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

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.

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.

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.

IMPLEMENTATION

- Our Total Cost (TC) function for EAACO and EAGA combines four critical factors for optimal route selection

  TC = (Distance Weight × Distance Cost) + (Weather Weight × Weather Cost) + (Elevation Weight × Elevation Cost) + (Fuel Weight × Fuel Cost)

- **Cost Function Components**
  - **1. Weather Cost Components**
    - Temperature Penalty: Applies when temperature exceeds 30°C:

      Cost = 0.05 × (Avg Temp - 25)²

    - Precipitation Penalty: Scales with rainfall intensity:

      Cost = 0.2 × Average Precipitation

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

      Cost = 0.1 × (Avg Wind Speed - 5)²

IMPLEMENTATION

  - **2. Elevation Cost**
    - Accounts for terrain difficulty:

      Cost = 0.005 × (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***

IMPLEMENTATION

- **Demand Forecasting using NeuralProphet**
  - The process relies on structured historical data, including timestamps, product categories, vendor behaviors, and seasonality.
  - NeuralProphet combines autoregression, trend and seasonality modeling, and neural networks to handle nonlinearities in vendor order trends.
  - Unlike traditional methods, NeuralProphet is robust to missing data and requires minimal preprocessing.
  - It adapts to sudden market changes, such as promotions or demand surges, using change point detection.
  - The model is trained on past vendor order data to predict future demand with high precision.
  - By factoring in holidays and seasonal effects, NeuralProphet enables suppliers to manage inventory proactively and optimize replenishment.
  - This approach outperforms traditional statistical models by offering flexibility, robustness, and better real-world applicability.

CHALLENGES

- Route optimization was difficult due to dynamic traffic patterns and time-sensitive deliveries, solved using EAGA with adaptive parameter tuning.
- Varying vendor availability made route planning unstable, addressed through mutation and elitism to maintain solution diversity.
- Incomplete and inconsistent historical order data reduced forecasting reliability, resolved using comprehensive data cleaning techniques.
- Order aggregation using DBSCAN struggled with manual parameter tuning, which we automated using a Genetic Algorithm.
- Ensuring Minimum Order Quantity (MOQ) in clustering was challenging, managed by integrating MOQ validation and marking unmatched orders for future aggregation.

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).

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
	350	0.010	98	219	0.355
GA-DBSCAN	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
	300	0.048	35	262	0.715
	350	0.055	45	301	0.629
K-means	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
	200	0.032	61	122	0.385
	300	0.007	84	189	0.363
	350	0.008	94	227	0.350
Agglomerative	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

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 \(\varepsilon\) and \(\text{min_samples}\), 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.

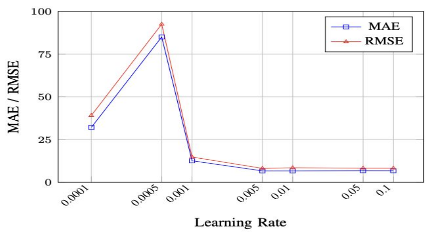
PERFORMANCE ANALYSIS

- **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

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.

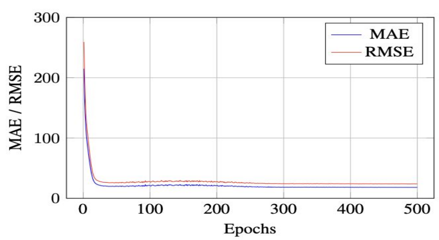


PERFORMANCE ANALYSIS

- **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).

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.



RESULTS AND INFERENCES

- **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.

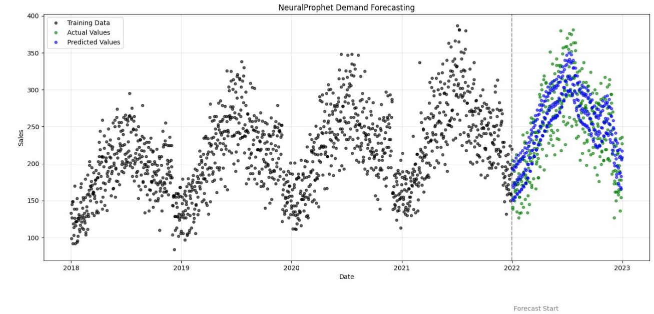
RESULTS AND INFERENCES

- **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%)

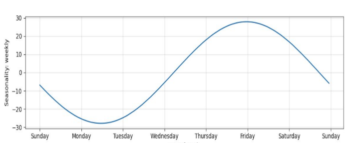
RESULTS AND INFERENCES

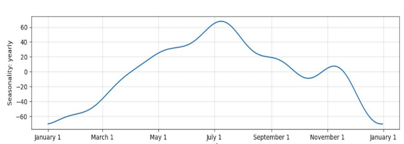
- **Demand Forecasting Capabilities :**
  - Figure illustrates NeuralProphet's ability to predict future order quantities based on historical data, providing vendors with reliable projections for inventory planning. Supporting this predictive capability



RESULTS AND INFERENCES

- **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.

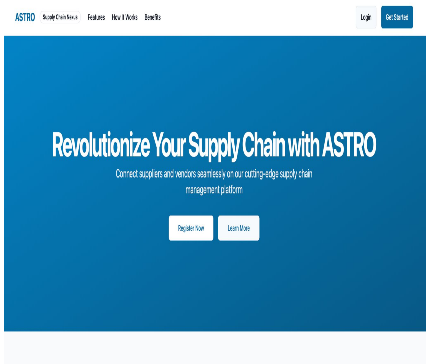


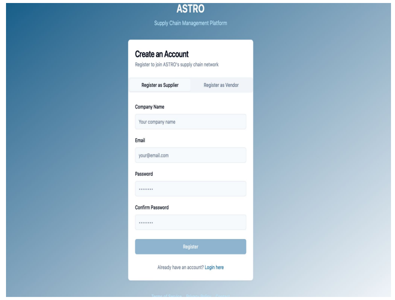


CONCLUSION

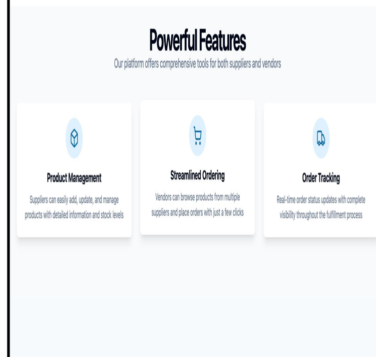
- **Summary of the Work Done**
  - ASTRO was developed to enhance procurement and logistics for small-scale vendors.
  - Implemented DBSCAN with Genetic algorithm for order aggregation, Environment Adaptive Genetic Algorithm (EAGA) for route planning, and NeuralProphet for demand forecasting.
- **Limitations 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.

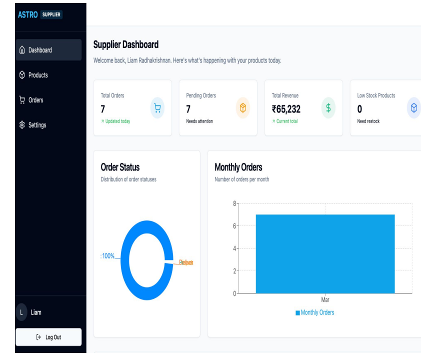
SCREENSHOTS



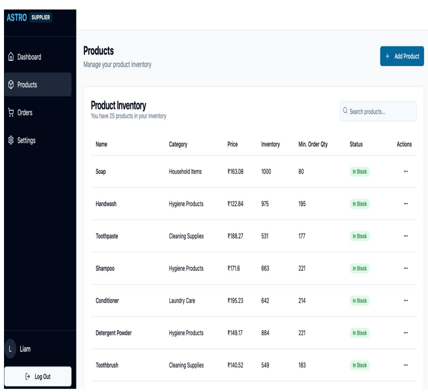


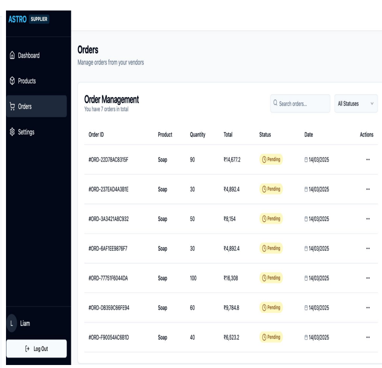
SCREENSHOTS



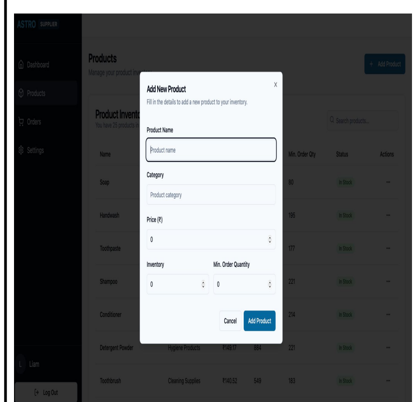


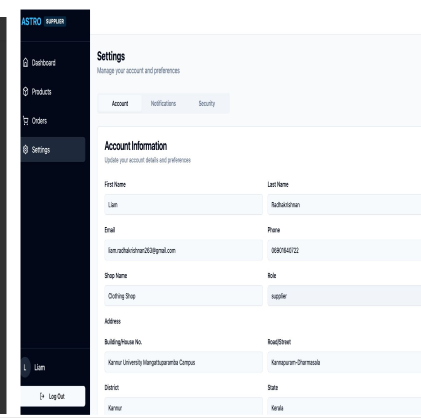
SCREENSHOTS





SCREENSHOTS





REFERENCES

- X. Wang and L. Wang, **“Green routing optimization for logistics distribution with path flexibility and service time window,”** in 15th International Conference on Service Systems and Service Management (ICSSSM), 2018, pp. 1–5.
- E. M. U. S. B. Ekanayake, S. P. C. Perera, W. B. Daundasekara, and Z. A. M. S. Juman, **“A modified ant colony optimization algorithm for solving a transportation problem,”** J. Adv. Math. Comput. Sci., vol. 35, no. 5, pp. 83–101, Aug. 2020.
- J. Zhou, **“Research on multi-objective green vehicle path optimization based on whale algorithm,”** in International Conference on Networking, Informatics and Computing (ICNETIC), 2023, pp. 385–389.
- K. A. Mamoun, L. Hammadi, A. E. Ballouti, A. G. Novaes, and E. S. D. Cursi, **“Vehicle routing optimization algorithms for pharmaceutical supply chain: A systematic comparison,”** Transp. Telecommun. J., vol. 25, no. 2, pp. 161–173, 2024.
- A. Maroof, B. Ayvaz, and K. Naeem, **“Logistics optimization using hybrid genetic algorithm (HGA): A solution to the vehicle routing problem with time windows (VRPTW),”** IEEE Access, vol. 12, pp. 36974–36989, 2024.

REFERENCES

- S. J. Taylor and B. Letham, **“Forecasting at scale,”** PeerJ Preprints, vol. 5, p. e3190v2, Sep. 2017.
- O. Triebe, H. Hewamalage, P. Pilyugina, N. Laptev, C. Bergmeir, and R. Rajagopal, “NeuralProphet: Explainable forecasting at scale,” 2021.
- X. Ai, Y. Yue, H. Xu, and X. Deng, **“Optimizing multi-supplier multi-item joint replenishment problem for non-instantaneous deteriorating items with quantity discounts,”** PLOS ONE, vol. 16, no. 2, pp. 1–22, Feb. 2021.
- S. B. Jouida and S. Krichen, **“A genetic algorithm for supplier selection problem under collaboration opportunities,”** J. Exp. Theor. Artif. Intell., vol. 34, no. 1, pp. 53–79, 2022.
- M. Seifbarghy, M. Shoeib, and D. Pishva, **“Coordination of a single-supplier multi-retailer supply chain via joint ordering policy considering incentives for retailers and utilizing economies of scale,”** Scientia Iranica, 2022.

THANK YOU