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# Customization of Time Slots for Delivery of Articles and parcels using Artificial Intelligence

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**Abstract—On demand delivery began as a competitive edge in the consumer market. Quick commerce sites provided customers access to products within the shortest possible time to stand out from rivaling brands. However, this fast growth of 10 minute and 1 day delivery services leave traditional delivery services irrelevant. Due to the customer's opting for convience and speed, retailers selling stock struggle to meet these expectations and lose profitability. Access to real time data updates and optimisation has hence become significant in ensuring delivery to correct locations, punctually and efficiently. Current local systems struggle to respond to dynamic data, leading to missed delivery time slots, manual intervention requirement, excessive fuel and time wastes, poor customer feedback and so on. In order to remain competitive in such consumer markets, business require real time updates on demand and supply chains, delivery agent availability, client shopping patterns and traffic volume information. To counter these challenges artificial intelligence can be used to understand real time data and set parcel delivery time slots automatically while routing delivery agents through optimal pathways and monitoring the system of the agents and customer to align with their available schedules. The AI will utilise previous ETA, traffic congestion, pattern recognition in relation to prior on time articles that were received and user presence to define schedules for delivery and update the consumers, drivers and supervisors accordingly. This proposed intelligent system would solve the common E-Commerce problems faced by traditional delivery systems by ensuring routes are mapped to avoid redundancy, increase time efficiency, deliver as per consumer availability, especially for cash on delivery where the client is required at the home for payment, provide real time transportation status of the products to supervisors and customers, therefore increasing the trust of the user in the brand and providing an avenue for the manager to handle mismanaged deliveries. Such a system would bolster customer satisfaction and also reduce fuel and time consumption for the drivers, enhancing their work life balance. Deliveries that are more likely to be missed or routes that could result in accidents would be information sent to the supervisor, customer and delivery agents respectively, hence, preventing missed deliveries, injuries and delays. Such systems have been applied experimentally at a smaller scale and proven successful in reducing time, fuel, costs and injury risk, while improving customer satisfaction, making them a worthwhile subject of research.**

**Index Terms—Last-Mile Delivery, Customized Time Slot Scheduling, Intelligent Logistics Systems, Delivery Route Op- timization, Machine Learning in Logistics, Real-Time Delivery Management, Vehicle Routing Problem, API-Driven Architec- tures, WebSocket-Based Communication.**

## I. INTRODUCTION

An expansion in a sector of the e-commerce industry has been noted in the quick commerce segment. Here customers expect delivery within minutes or days. In the past when customers would buy things with long term plans in mind, such speed was unnecessary, but due to the increasing profitability of capitalising on impulse purchases. Consumer behaviour is shifting towards immediate gratification. Fast deliveries conveniently arriving at customer door steps have become a necessary feature for e-commerce retailers in recent years.

However, this boom gives rise to significant challenges. Delivery agents struggle to meet the tight deadlines provided for deliveries of products. Some meet accidents or over work themselves just to keep up with the deliveries. Some customers may order essential items like medication that if delayed could exasperate their health conditions, while others may lose trust in their business due to failed deliveries. Supervisors are concerned about the brand reputation being a stake with every delivery made. Conventional systems fail to meet these ex- pectations as they require real time data required for dynamic decision making.

This paper focuses on a project that uses AI to solve this issues from all three angles. It provides customers with real time updates on the status of their ordered products as well as notifications in advance, in case the delivery is more likely to fail. It considers conditions like the road, weather, nearby delivery locations, customer availability and so forth, allowing the delivery agents to deliver at times the deliveries will not be missed. It optimises routes to deliver to multiple locations within a smaller pathway, there by saving the driver fuel and time as well as reducing the risk of accidents. Finally it provides the administrator an overview of the system they are responsible for, reducing friction between their understanding and the deliveries being made.

## II. LITERATURE REVIEW

Several studies have already focused on this research but they tend to focus on one specific aspect. A collaborative system that is designed for the user, agent and the supervisor are yet to be improved. Early research has focused on vehicle routing problems, time constraints, distance minimisation, time efficiency, operational costs and so on but failed to apply the tools discovered in a manner benefiting the trifecta of the user, agent and supervisor.

The research also primarily focuses on mathematical programming conditions including formulas, heuristic algorithms, etc, that are not apt for supporting the dynamic information of the unstructured data, necessary in the practical aspect of delivery. Prior lack of investment and development in hardware required for computation has also left older systems reliant on algorithms designed for computational efficiency instead of accuracy.

Metaheuristic algorithms like genetic algorithms, tabu search, etc, are less accurate compared to the modern advancements like logistic regression, clustering, random forest and gradient boosting. Although the previous algorithms were applicable for lower data points, we have access to more data than ever before, as more consumers are present on e- commerce platforms now. Hence a system that utilises this newer data to predict the ETA using historical traffic data, GPS tracking previous delivery logs and other information via machine learning systems and cloud databases is necessary for improvements in the e-commerce sector.

## III. BACKGROUND AND PROBLEM CONTEXT

Due to recent shift in customer behaviour, availability of e-commerce platforms encouraging fast deliveries to remain culturally relevant, and profitability of impulse purchasing power in an ever growing digital consumer population, last mile delivery within a small span of time has become essential for digital businesses to not lose their competitive edge.

The recent ethical debates over the delivery agents safety, customer’s concerns after paying for their orders that they did not receive on time, especially on express shipments, and pressure from the external market to maintain trust, all create potential problems for quick commerce platforms promising speedy deliveries, as even a single missed order can permanently damage a customer’s trust, even a single delivery driver accident can cause protests and legal regulations on the business and these can mount up into catastrophes causing business failure.

Despite these challenges, fast e-commerce delivery has become an integral part of the majority of the market. As such businesses that fail to adapt and continue to use traditional systems for delivery require updation in order to survive.

**Evolution of Intelligent Delivery Systems**
The way delivery and logistics work has changed a lot because of the growth of online shopping, the way customers now expect service, and the need for better efficiency. Over time, delivery systems have moved from old, simple methods to smart, AI-powered systems that make decisions on the fly.

**Traditional Logistics Systems**
In the past the delivery systems were often simplistic. Agents witnessed updates via sight or through the police or construction crews and evaluated the alternative routes for delivery, based on their own memory. Customers received their products at a previously agreed upon time, with the business. Then came improvements in computation that resulted in heuristic algorithms like Dijkstra’s, A*, travelling salesman, and so on.
These algorithms were enough to deal with simple static data on roads that rarely developed, and traffic that was slow moving cars or bicycles. Overtime CCTV cameras, speed sensors, road safety improvements, infrastructural promises by politicians resulting in development and

ongoing construction, high speed vehicles like sports cars and bikes, all became common place, providing potential for improvement.

Consumer data gathered by e-commerce businesses, GPS tracking via satellites, internet traffic, increasing numbers of consumers utilising digital shopping all exploded in recent years. This provided information to algorithms that could use machine learning for prediction via pattern recognition. These machine learning algorithms could predict the customer availability, best routes, accident risk, potential delays and more, before they even happened, allowing changes on the fly.

Current delivery agents are also present in the form of drones, self driving cars and other AI devices, reducing the manual and human intervention that used to be required during deliveries. Advancements to such systems will result in the fastest e-commerce with the highest convenience humanity has yet to see.

These old systems had some big problems:

- Too many failed deliveries
- No real-time information for the people in charge
- Little or no chat between customers and delivery people
- Wasted use of delivery resources
- As more deliveries happened, these systems had trouble keep- ing up with the changing needs of customers.
- Rule-Based Scheduling Approaches

Companies began using rule based approaches to improve their current systems. These rules included:

- Fixed time slots for delivering products
- Deliveries being grouped by the area
- Prioritising deliveries based on products, for example delivering perishables first to avoid spoilage
- Despite this assistance in automation, the rules remain rigid and fail to adapt to dynamic conditions like bad weather, road congestion, customer availability and whether delivery agents were free. These situations required human expertise which slowed down the delivery process, making delivering human extensive and scale difficult to achieve.
- Transition to AI-Driven and Data-Centric Systems

In the current day delivery systems are approaching the intelligent era where they utilise the listed data to train automation models:

- Past successful or missed delivery data
- Customer availability
- The times and locations of deliveries assigned
- Route details for the delivery assignments for optimizing travel

These are fed into AI tools to predict delivery slots with higher chances of success. Real time sensors and communication channels provided constant updated data allowing changes if required.

Such advancements help with:

- Matching the delivery time to when customer is present, thus, reducing missed delivery chances
- Increase in customer satisfaction
- Informed business decisions
- AI training improves with higher data quality leading to better results.

**Static Scheduling and Dynamic Scheduling**

A significant alteration in delivery system structure involves the switch from static to dynamic deliveries. Static systems are rule based while dynamic systems consider the changing situations before outputs, improving the flexibility of modern day delivery systems.

Techniques and Conceptual Approach

Artificial Intelligence is a very important tool in the process of delivering packages at the right time. It assists in predicting when the delivery will take place, combining deliveries, creat- ing the best schedule, and making intelligent decisions. For a delivery system, its components include the supplier, consumer and the delivery agent. A connection is essential between all three, as the system fails if even one of the components fails.

Hence, this project focuses on all three as follows:

**Supplier**

The supplier is provided with the schedule of the delivery agent. They can select which agent to assign to which task ensuring that the deliveries are not repeated or left undelivered. An XGBoost algorithm is built to assist in the selection of the agent, based on the agent availability within the location, the time that the customer would prefer the delivery in, and it also includes a risk assessment for failure of delivery so that they supplier can avoid assigning them in case of low feasibility.

**Consumer**
The consumer is provided with the arrival time of the delivery agent and an option to choose a different time slot based on their convenience. This system ensures that parcels will not be left undelivered in case of cash on delivery purchases. An XGBoost algorithm is also used to assist in the selection of the time range, based on the customer's previously completed deliveries. This reduces the chances of a failed delivery and increases the customer satisfaction and trust in the brand.

**Delivery agent**
The delivery agent is provided with multiple deliveries assigned optimally by the supervisor. A VRP algorithm is used to calculate the most fuel and time efficient for the driver while hitting multiple drop locations in the same pathway. The algorithm also calculates risk of accidents on pathways to avoid high risk regions. This reduces working hours for human drivers and operational costs and emissions for robotic agents.

These systems are integrated into a UI which uses HTML, Javacript and CSS for proper formatting, user friendliness and an appealing design. SQL lite is used as the database for the storage of training algorithm data. Python and it's libraries are used for the algorithms mentioned.

## VI. COMPARATIVE DISCUSSION AND ADVANTAGES

**Operational and Customer-Centric Benefits**
By allowing customers to choose their preferred time of delivery, the system will minimize the number of failed deliveries.

AI will assist in grouping deliveries more effectively and routing them in a better manner, making the entire process smoother.

This technique optimizes the use of delivery resources, reduc- ing unnecessary trips and saving money in the process.

Customers will be satisfied with the delivery times and will be able to adjust their schedules accordingly.

**Practical Feasibility**
The technique applies AI algorithms and optimization techniques that are already in common use.

The system is built in a modular fashion with APIs, making it easy to integrate with the existing delivery services.

The system can be implemented incrementally and will work well for both small and large delivery services.

**Comparison with Traditional Delivery Systems**
One of the biggest changes in the delivery systems is the transition from static scheduling to dynamic scheduling. Static scheduling is rule-bound, whereas dynamic scheduling involves changing as things unfold. This is a big leap towards making the delivery system smarter and more flexible.

**Advantages**
The proposed machine learning system is advantageous in the following ways:

It uses real time data for analysis which allows it to make decisions based on the most updated situation.
The training and testing sets are of higher quality due to global cloud based databases allowing international data access and adaptable intelligence.

**Table I**
**Comparison Between Traditional Systems And Machine Learning Systems**

| Category | Traditional Systems | Machine Learning Systems |
|---|---|---|
| Data Characteristics | use static data for anal- ysis | use real time data for analysis |
| Data Volume | have limited data due to conventional on premise storage methods | have higher amount of data due to cloud based databases |
| Output Timeliness | may provide outdated output as they use his- torical data | more likely to provide updated output as they use historical and real time data |
| Output Usability | output provided is | output provided is eas- ier to apply as |

| | | |
|---|---|---|
| | dif- ficult to apply | it is des- ignated based on pur- pose |
| User Interface | interface requires spe- cialised training which may not be possible for a delivery agent, customer or adminis- trator | interface is user friendly and comes with a tutorial which makes it accessible for a delivery agent, customer and administrator |
| Component Design | components may not be useful due to lack of user friendly design, for the intended indi- viduals | components are useful as they are tailored for the intended individu- als |
| Robotics Integration | cannot integrate with robotics | can integrate with robotics |
| Accuracy | may provide inaccu- rate results due to lim- ited data which is out- dated and or static | more likely to provide accurate results due to larger amounts of data |
| Cost | cheaper as it requires hardware most busi- nesses already possess | may be more expensive as it requires cloud technologies, AI computation, etc |
| System Maturity | developed, and under- stood by technicians | still under development, plenty of room for improvements |
| Maintenance | requires lesser main- tenance of the sen- sors and data collec- tion units as the data is historical | requires more main- tenance of the sen- sors and data collec- tion units as the data is real time and issues with the sensors can cause problems with the updates |

Synthetic data sets can be used based on patterns to protect user privacy.

Output is divided for intended individuals making it easier to apply.

The interface is user friendly and comes with a tutorial to make it easier for the agent, customer and administrator.

Since this is AI powered system it has the potential to integrate with robotics to allow delivery with drones, self driving cars, etc.

The larger database means the quality of the results can be more accurate.

## VII. METHODOLOGY

The methodology includes the use of machine learning to generate predictions, front end user interfaces to frame output in an applicable manner and optimisation based on testing and training data sets.

**Step 1: Data Collection & Preprocessing**
Various sources are used for data collection, including:
Traffic data: road closures, distance between locations, traffic congestion, estimated arrival times, etc.

Environmental reports: weather reports as bad weather can impact navigation, condition reports, especially for last mile deliveries where roads may be absent, etc.

Previous delivery logs: missed deliveries, customer availability at different times, earlier tasks assign to delivery agents, warehouse locations, etc.

Current delivery logs: time slots if customer has selected any, delivery agent working hours and current location, etc.

After it is collected it is stored in the model's format to allow for smoother training application.

**Step 2: Model Selection**
A hybrid approach for model selection was used. The vehicle routing problem algorithm is used for the delivery agents and the XGBoost algorithm is used for the customer and administrator/supplier predictions.

XGBoost for customers: Here the XGBoost customer model assists in the selection of the time windows for a successful customer delivery, based on provided data. Here, XGBoost is picked as it is good at solving probabilistic pre- diction problems like time slot prediction, using apt handling of nonlinear, missing or noisy data sets.

XGBoost for suppliers: Here the XGBoost supplier model assists in the selection of the delivery agent for a specific delivery ensuring deliveries aren't repetitive or left undelivered. It also includes a risk analysis to check potential for a failed delivery so suppliers avoid assigning them if they're not feasible. Since this is a feasibility and ranking problem, XGBoost excels using multiple factors for decision making and calculating the risk score. It also produces more interpretable output compared to neural networks.

VRP for delivery agents: Here the VRP model assists in the selection of the routes for delivery based on the time windows predicted by the XGBoost for customers, previous deliveries assigned, fuel and time efficiency for the driver, other drop locations in the same path, and risk of accidents to avoid high risk areas. VRP is applied here as this is a combinatorial optimization problem with solutions that might change based on dynamic updating. This model supports time windows as a constraint, allows for risk aware routing, and workload balancing. It has already proven itself in industries utilising vehicle routing to fix airline problems, transportation, etc, making it a suitable model.

**Step 3: Model Training**
Synthetic data is generated by patterns found in real data to protect privacy. Previous real data collected can also be used after approval. These datasets are divided into training and testing data.

The training data related to customer availability, prior missed and successful deliveries, etc, is provided to the XG- Boost model for customers, current driver location, working hours, assignments, undelivered items, and other such data is provided to the XGBoost model for administrators.

Lastly, routing data including traffic congestion, weather reports, road closures, etc, is provided to the VRP model. All the models are then trained on their respective data sets.

**Step 4: Model Testing & Optimisation**
The models are then tested based on the testing data and optimised accordingly to ensure higher accuracy. The testing involves setting constraints for expected accuracy and generation of classification reports with a emphasis on the important metrics.

Optimization can include various iterations for further train- ing, generation or collection of new data and pre processing to remove noise from data if there's under fitting, reduction of model complexity in cases of over fitting, and so on.

**Step 5: Prototype Deployment**
React.js is used to provide a dynamic user friendly inter- face that has an appealing design with a tutorial for proper usage of the application. The prototype is then deployed to a structured GitHub repository with instructions for running and maintenance or via a web domain application. System Architecture and Module Identification Frontend (Web Application)

The front end of the system is a web application that has interfaces for the consumers, supplier and then delivery agent, based on the individual's intended role.

**Technologies Used:**
React.js: it builds the dashboards for the administrator that is supplier, customer and delivery agent to allocate delivery select time slots and view the optimised routes respectively.

Mapbox API/Google Maps API: visualises the map to display the route and it's used for location tracking of the parcels and agents.

A singular front end provides different screens on the basis of the role of the user to ensure consistency while still providing ease of maintenance and customization based on the user.

**Backend (Simplified Microservices)**
The back end uses Python for development of the machine learning models, routing algorithms and API services. It also integrates them to provide a smoother system experience.

**Technologies Used:**
FastAPI: is used to build REST APIs to provide com- munication between the front and back end. It also generates trained machine learning models to provide

estimated time of arrival, time slot recommendations and risk analysis of the routes for delivery agents.

VRP: the vehicle routing problem algorithm uses time window constraints and a Python based routing algorithm to predict the optimal routes for delivery agents.

JWT: JSON Web Tokens are used during the login and sign up for authentication and role based access authorisation.

Celery with Redis: it's used to handle asynchronous tasks like routing updates and notifications and background model processing of changes.

This approach keeps the system simple, yet modular to make edits easier.

**Databases**
The system uses multiple databases to efficiently handle different types of data.

**Databases Used:**
PostgreSQL: it's a structure data storage for information on orders, users, previous successful and unsuccessful deliveries as well as time slot preferences of the customers.

MongoDB: stores unstructured or semi structure data that is delivery logs, feedback from customer, dynamic events like changes in the environment and monitory comments by supervisors.

Redis: caches and handles real time updates, including live ETA and session logins, time windows and other information.

**Machine Learning and Optimization Stack**
Machine learning and optimisation methods form the core of this intelligent delivery system.

**Models and Algorithms Used:**
LightGBM / XGBoost: these are used for estimating time of arrival and delays that might occur during the delivery.
Logistic Regression and CatBoost: these are used for predicting the chances of successful delivery for a given time slot based on the customer's availability.

Logistic Regression: it's used to protect if a cash on demand delivery will be successful on the basis of probability of previous successful and unsuccessful deliveries, as these deliveries require customer presence making them higher risk.

Isolation Forest: is used to detect anomalies in delivery patterns or environment that can result in deviation from estimated times.

Heuristic-based VRPTW algorithms: vehicle routing problem with time window constraints uses heuristic approaches to optimise routes by constraining itself to the time slots selected by customer.

Deep Q-Network (DQN): used to simulate environment for reinforcement learning based route optimisation in case of previous algorithm failure due to anomalies.

High accuracy prediction, intelligent time slot selection and allocation of delivery agents, efficient routing that ensures proper delivery times are all possible due to the collective usage of these models in the system.

## VIII. CHALLENGES AND FUTURE SCOPE

**Challenges**
There are many challenges that require resolution during the creation and maintenance of such a system. Some of them are listed below:

- Accountability: although the final decision rests with the managers, them choosing to auto pilot the suggestions instead of reviewing them can cause errors in assignment.
- Complexity of the models: as there are multiple models used for multiple interfaces, integration across them poses a challenge.
- Data privacy: even usage of synthetic data such cannot guarantee highly accurate results, therefore some real user data is required and poses questions for privacy.
- Ethical concerns: if the delivery agent module is upgraded to integrate with robotics and replace human drivers, it can cause concerns related to job loss.
- Result accuracy: the results are highly dependent on the computational abilities and complexity of models, which are dependent on the data sets provided. Errors in any of these situations can provide inaccurate results.

- Upscaling: at a smaller scale the system is budget friendly, but the computational requirements and maintenance of such a system for the millions of users purchasing from e-commerce giants may cause cost to scale before profit.

**Future Scope**
The future scope for this system is vast:

- The XGBoost algorithm can also be modified for customer retention, suggestions for new products based on past experiences, and so on.

- The VRP model can we utilized in different sectors like the health care industry for ambulances, to provide optimal routing even in emergency situations. It can also be updated to enhance a driver's work life balance.

- The datasets can be revised to include information associated with types of products delivered, quantities of products delivered or out of stock, etc, and fitted into XGBoost algorithms to provide supply chain planning.

- Warehouse locations can be added to VRP to include the pickup times and regions to optimise pathway selection further.

## IX. CONCLUSION

This project focuses on an AI system that assists in delivery time slot scheduling using real time data to fix the issue of last mile logistics, particularly in cases a customer may not be available to receive deliveries, or high risk areas where delays would be expected. The project uses machine learning algorithms for prediction, REST APIs for instant communication and a division of roles among the users to adapt the workflow to their custom needs. Such an organisation improves delivery success and operational efficiency.

Conventional processes involve usage of fixed time slots and sending notifications after shipping which may fail to reach an absent customer leading to their deliveries being missed.

The proposed project provides an instant communication flow through WebSockets, between the supplier, delivery part- ners and customers, preventing early or late shipping.

The supplier assigns deliveries based on requirements and customer availability. Delivery partners can check efficient routes that hit multiple drop locations at once and leave only after customers approve of delivery times. All the updating and changes occur instantly across dashboards to ensure clear communication and failures due to misunderstandings are reduced.

A random forest training model is used to predict the appropriate delivery timings based on historically successful delivery data. These time windows reduce repeat attempts and plan right routes, boosting delivery driver and customer satisfaction, which improves business reputation.

The modular approach to system building leaves it open to new improvements and features like chatbots and live location for future advancements based on feedback and investment provision.

This project is a testament to how useful AI systems can prove when combined with real time sensors to improve the delivery process compared to traditional static systems.

The solution provides scalability, operational efficiency, cost reduction, and dynamic logistical analysis capabilities, making it a good starting point for future research, particularly in the intelligent e-commerce delivery silo.

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