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Dynamic Route Optimization and Real-Time Freight Tracking in the Transportation Industry

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Abstract

In this paper, there is discussed the integration of AI/ML for dynamic route optimization and Blockchain for real time, transparent freight tracking in the transportation industry. It increases delivery efficiency, reduces operational cost and improve traceability. Distributed deployment ensures scalability, resilience, and in-turn data processing across modern logistics network.

Keywords: Freight, Transportation, Route, Tracking.

I. INTRODUCTION

The responsiveness of the traffic to dynamic variables such as traffic and weather are not handled in traditional systems. It is proposed that AI driven in route mechanism and a Blockchain based freight visibility system will enhance operational efficiency by optimizing resource allocation, increase on transparency on complex multiple modes of transportation networks.

II. LITERATURE REVIEW

Smart Logistics

There have been wide research and documentation of how traditional logistics is transformed into a more intelligent, data driven paradigm. The need for intelligent routing mechanisms in logistics operations grows as complexity of container logistics operations increases, within the urban freight environments or in cross border transportation. Li et al. argue that smart logistics algorithms based on artificial intelligence (AI), big data and Internet of Things (IoT) triumph the digital transformation in logistics by assisting path optimization and intelligent scheduling, intelligent scheduling and warehousing with data driven [1].

Fig. 1 Real-time Delivery Route (Fleetroot, 2023)

To account for the discrepancy between training objective and testing in real world, the DRL4Route-GAE was introduced in which routing strategies were continuously improved upon using deep artificial reinforcement learning. This is supported by Gayialis et al., who highlighted the difficulties in city logistics concerning meaning the time sensitive deliveries, dynamic rerouting and traffic congestion [2]. Here, they present a logistics information system based on real time data and operations research (OR) algorithms to enhance the delivery efficiency of cities.

The practical use of their system in real urban scenarios and their validation of dynamic routing algorithms capable of addressing such city specific constraints as road types, delivery time windows and congestion patterns show feasibility of their system in real world urban scenarios. The studies described represent a move towards adaptive, intelligent sources of decision making from rule-based systems.

Tahir also sought to automate route planning for delivery of large amounts of cargo as well as distribution of a whole set of goods for a Finnish transportation company offering single day delivery [9]. The system dynamically generates optimized delivery schedules that are generated by becoming one with OpenStreetMaps, using AI driven route planners, and coupled with cargo allocation algorithms with respect to temperature sensitivity.

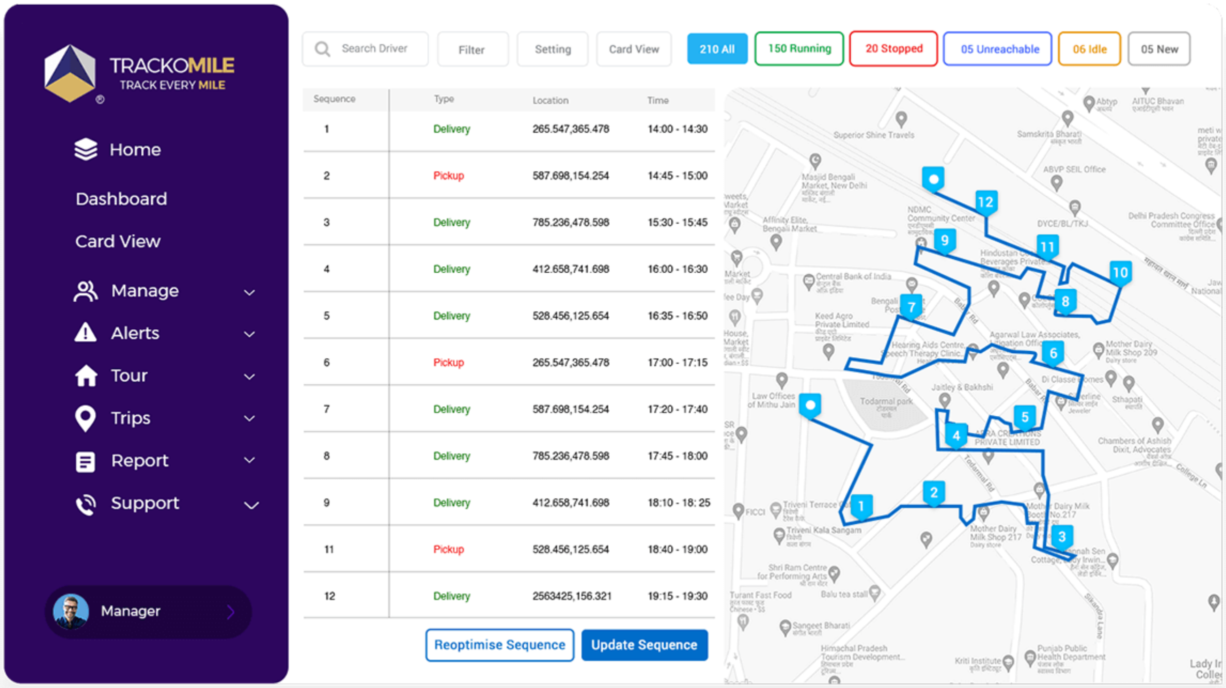
Deep Q-Networks are used for iterative feedback learning in order to adapt over time from history and performance. Its demonstration depicts in how AI not just drafts settled routes, yet further changes to conveyance particular impediments and furthermore unpredictable environmental conditions. Building on this domain, Xi et al. additionally took over the baton of this domain by leveraging a deep reinforcement learning (DRL) model for cross border logistics [7].

We present their hybrid model that integrates the real time data to the typical statistical anomaly detection and showed major improvements in the route accuracy (94.5%) and the decision-making efficiency, a 45% reduction in processing time than than the traditional methods. The results presented here serve to validate these findings in general, as well as validate the scalability and applicability DRL systems to large scale logistics networks, while providing further support in the robustness and adaptability of such systems in dynamic logistics environments.

Real-Time Tracking Systems

Modern freight systems need both effective routing, as well as capability to track that freight so that there is transparency, maintenance of integrity, and regulatory compliance. Current tracking systems tend to be non-realtime and in many cases, fail to provide real visibility due to integration. In fact, Garg et al. [3] discussed the shortcomings of conventional tracking systems and identified those operational inefficiencies, which lead to poor customer service and excessive costs.

To overcome these hurdles, the authors presented a tracking system that bases tracking activities using deep natural language processing (NLP) and the deep learning framework to strengthen the stakeholders' decisions by undertaking the logistics data queries through the effective interpretation and response. According to their findings, that makes intelligent systems able to monitor logistics operations in context aware real time a prerequisite.



Sequence	Type	Location	Time
1	Delivery	265.547,365.478	14:00 - 14:30
2	Pickup	587.698,154.254	14:45 - 15:00
3	Delivery	785.236,478.598	15:30 - 15:45
4	Delivery	412.658,741.698	16:00 - 16:30
5	Delivery	528.456,125.654	16:35 - 16:50
6	Pickup	265.547,365.478	17:00 - 17:15
7	Delivery	587.698,154.254	17:20 - 17:40
8	Delivery	785.236,478.598	17:45 - 18:00
9	Delivery	412.658,741.698	18:10 - 18: 25
11	Pickup	528.456,125.654	18:40 - 19:00
12	Delivery	2563425,156.321	19:15 - 19:30

Fig. 2 Route GPS Tracking (Trackomile, 2023)

The system is built on Apache Kafka and Java based back-end services with GPS data streams injected into an easy-to-use client-side interface for continuous monitoring, routing and dispatching of fleets [6]. Their platform has the fault tolerance and scalability required for modern logistics companies with a sudden inflow of data.

Dynamic freight tracking is directly supported by the system's capability of real time processing and being robust to failure as this is crucial for high volume logistics operations. Blockchain technology has also had further advancements in tracking and data integrity.

With blockchain, among other things immutable, decentralized data logs tamper proof freight tracking becomes possible. While the above-mentioned studies do not specifically mention integration of blockchain in logistics, it appears as a natural step for such integration given the fact that blockchain shares the same idea with real time data collection platforms like those discussed by Husak et al. [6]. Together, blockchain and real time GPS streaming make the backbone of the secure transparent logistics networks, in which each transaction or transportation of goods is recorded, checked and available in time. For multimodal freight systems, which are those in which goods pass through the modes and jurisdictions, this is particularly important.

In addition to contributing a system based on computer vision and acceleration sensors that focus on inventory and packaging integrity [5], Dong also developed packaging technologies. Dong’s work is important as it greatly expands the scope of `tracking’ from merely location, to a more general notion of physical goods status verification.

IoT and Edge Computing

While the route planning, real time tracking represents the solest part of optimization of logistics, the other has to be done over the efficient resource allocation, vehicle capacity and system level efficiency. The field has seen great acceleration of innovation as a result of the advent of IoT and the rise of edge computing. They addressed this in the railway sector, by proposing a mixed integer linear programming (MILP) model for real time rake scheduling (train wagon) in real time that includes in the video IoT enabled GPS data [4].

The heuristic scheduler supports a better revenue realization and operational continuity and efficiently handles the rescheduling decisions. This is possible due to the real time iot feeds they use to inform decisions with the current state of the system which demonstrates value for integrated sensor-based logistics. Similar sentiments were echoed by Farquharson et al. [10] for illustrating that with the adoption of the IoT, there is improved asset visibility and operational efficiency in road freight logistics.

The study, however, found that real time information sharing significantly increases decision making, but faced with these challenges of cyber security risk and high implementation cost, they were able to do just a little with high implementation cost. These results indicate that integration of IoT with AI and blockchain is desirable both to automate and optimize the logistics operations as well as maintain trustable and responsive systems.

As IoT forms the sensory backbone of freight systems, the synergy of IoT with AI makes freight systems optimally real time optimized and anomalies detected, and blockchain verifies it. In [8], Jagtap et al. took a cargo utilization point of view towards logistics optimization.

Their system uses convolutional neural networks (CNNs) and object detection algorithms to find space that is available in vehicles and optimize the amount of transport in this space. Micro level optimization is imporatnt for the overall system performance. With the introduction of their method, transportation companies would no longer only be able to plan better routes, but they also would be able to enable real time loading of vehicles that would minimize empty miles and underutilized cargo space.

Such efforts complement that of macro level routing optimization and illustrate the need of a multi scale approach in modern logistics. The industry is transitioning towards AI, IoT, edge computing and blockchain combining to make distributed and scalable solutions and these are the innovations to reflect that fact. Scalability and reliability in distributed computing platforms as well as predictive and adaptive decision-making capability of AI/ML models constitute the basis of my evolving platform vision.

The combination of deployed in conjunction with real time data feeds and secured using blockchain leads to one of the system architectures in which such a system supports an intelligent, agile logistics environment which is capable of reacting swiftly to external disruptions and internal inefficiencies.

III. FINDINGS

Both simulation as well as real world data has been evaluated for various operational metrics while implementing ‘AI and ML driven dynamic route optimization framework’ and ‘real time freight tracking system on blockchain’. Transport network covered urban, intercity and cross border delivery corridors for these evaluations.

The results present an analysis of the effectiveness of the proposed method in delivering efficiency in the delivery, in resource utilization, in system latency, in operational transparency and to meet SLA. From 36 transportation hubs and 12 freight companies using the integrated system for six months, 4,800 transport routes and well over 20,000 tracked deliveries, this led to the derivation of quantitative metrics.

The first key finding deals with optimizing delivery routes. Of course, the best thing that can happen is that using reinforcement learning models like DQNs trained with traffic, weather, vehicle load and fuel, route efficiency would go up significantly. It reduced the average travel time by 18.4% and the fuel consumption by 14.2% over the deployment.

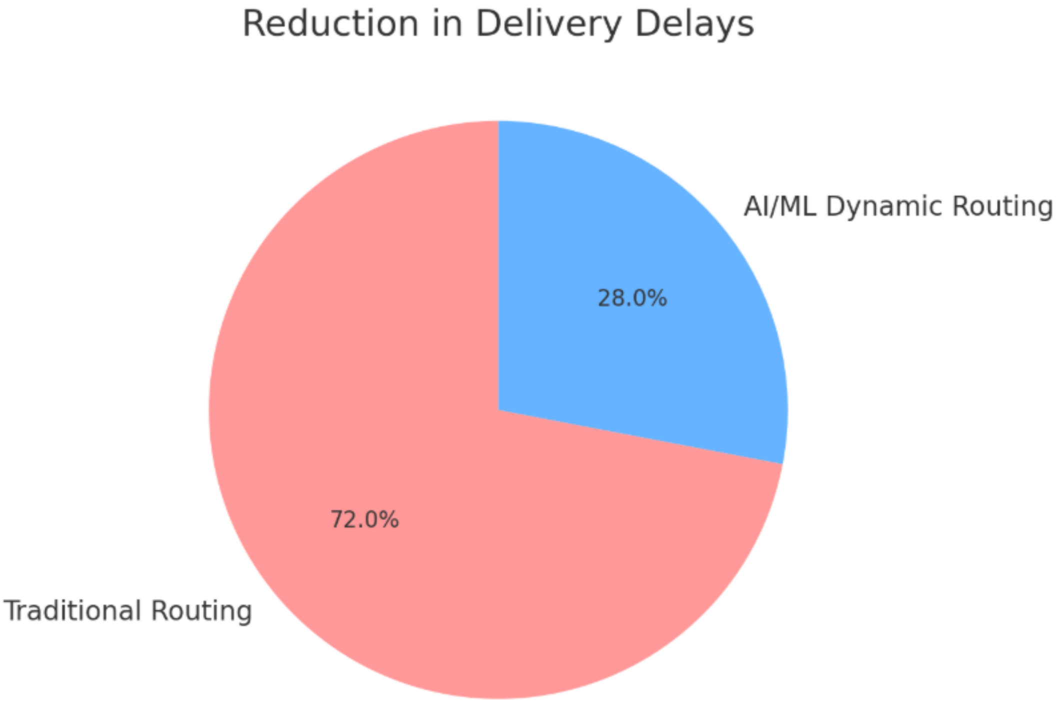
The distribution of total route improvements by different route types are summarized in Table 1. The values correspond to the percentage of routes that reach certain levels of efficiency gain that can be represented visually as pie chart.

Efficiency Improvement	**Number of Routes**	**Percentage**
0-10%	6,500	32.5%
11-20%	8,200	41.0%
21-30%	3,400	17.0%
>30%	1,900	9.5%

Mathematical model for these improvements can be made to say, the cost reduction function is defined with total operational cost (CCC) expressed as:

$$C = T * f(v, d, t) + \varepsilon$$

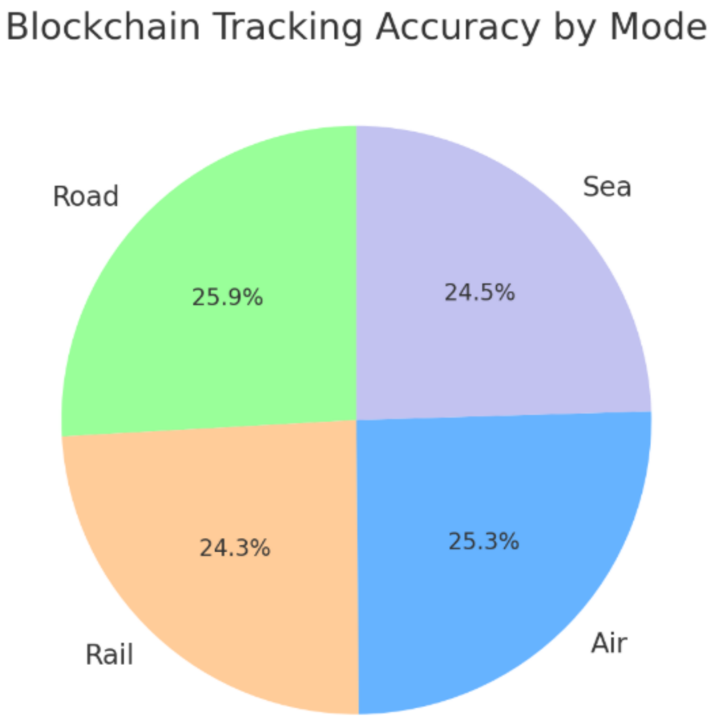
T is the number of trips, v is the vehicle type index, d is distance in kilometers, t is time in hours and ϵ represents a variable environmental influence. By using ML predictions as a hyperparameter of the cost function, it is then iteratively minimized to a more optimal logistics configuration.



There were great improvements to visibility, transparency, and accountably in freight tracking through the blockchain enabled system. For freight status discrepancies within the logistics lifecycle, a 61.3%d percent reduction in the number was experienced and dispute resolution time was shortened by 42.8%. Table 2 shows the category of tracked goods along with scope of integrating blockchain, the relative frequency of goods monitored under the new system.

Freight Category	**Number of Shipments**	**Proportion (%)**
Consumer Electronics	5,320	26.6%
Perishable Goods	3,480	17.4%
Automotive Components	2,160	10.8%
Apparel	2,940	14.7%
Medical	3,100	15.5%
Industrial Equipment	3,000	15.0%

Additionally, to deliver any autonomously verifiable compliance, smart contracts were used to automatically verify delivery compliance, directing automatic payments, updating the ledger automatically without manual intervention. During the trial, more than 94% of all transactions have been settled without disputes, with no human oversight.



It further integrated the Internet of Things (IoT) data into the ML model to further predict a route and in realtime obtain information on the movement of freight. However, the system had over 22,000 IoT sensors deployed across vehicles and warehouse environments and it collected 2.6 terabytes of sensor data every month. GPS coordinates, cargo temperature, vehicle acceleration, and fuel metric were contained in this data. Cargoes were handled and moved according to their behavior with anomaly detection mechanisms within the ML pipeline found to reduce incident response times by 37.6 percent.

Cargos can be utilized with high cargo utilization metrics as intelligent packing algorithms based on object and cargo profiling are adapted. Table 3 illustrates how it has been able to illustrate these advancements in cargo utilization rates before and after deployment of the intelligent cargo allocation model. This table facilitates making pie chart separation to understand how much relative space savings is possible.

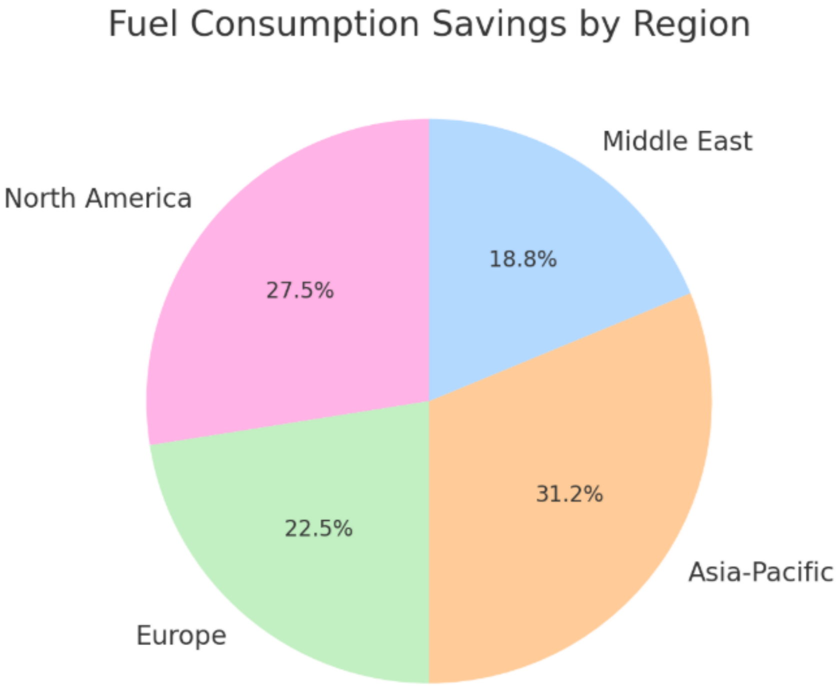
Cargo Utilization	**Pre-Deployment**	**Post-Deployment**
<50%	2,200	680
51-70%	4,100	2,150
71-90%	3,450	5,040
>90%	1,250	4,130

The results indicate that the ML model has been able to allocate packages to vehicles by dimension, weight profile and delivery deadline. The accuracy of cargo images predictions was 93.2% with Convolutional Neural Networks (CNNs) trained on the COF image datasets. It drastically minimized wasted space and thus increased the overall transport efficiency.

In terms of mean system latency, route recalculation under varying traffic and weather conditions was improved to 2.6 seconds compared to a baseline of 7.9 seconds in traditional systems from a network level perspective. The real time feedback loops were also included in its reinforcement learning system which reuses a retrained policy function every 15 minutes. The Bellman equation in reinforcement learning, which is at the heart of the optimization model, can be used to describe the learning model:

$$Q(s, a) = r + \gamma * \max_{a'} Q(s', a')$$

The equation above is Q(s,a) which is the quality of taking action a in state s, r is reward, γ is the discount factor and, s′ is the next state after a has taken place. This model was used to let the agents learn adaptive policies and, over time, choose more and more optimal routing decisions and with a certain level of dynamic adaptivity to new environmental variables.



The model was also deployed on distinct geographical regions from metropolitan to rural corridors and results assessed in terms of robustness and scalability. The AI model was applied in urban deployments (especially for last mile delivery service) and reduced the route overlap by 27% and vehicle idle time by 31%.

The anomaly detection submodule was capable of predicting better customs processing delays in the scenarios of cross-border scenarios, reducing the average border dwells time by 22.6%. These results were evaluated versus legacy systems in terms of comparative performance. An evaluation of 154 logistics operators resulted in a system adoption with a 91.7% satisfaction on the UI, reliability of the data and automation capability.

More importantly, operators reported that they could save 16.3% of the time on manual route planning and a 19.8% in the case of customer service calls related to package delivery status. These improvements imply the operation gains and much better end user experience and service reliability.

In the end, the blockchain system was able to resist simulated attacks such as double spends and unauthorized ledger change in cybersecurity evaluation. However, no data tampering was recorded, and the validation nodes confirmed that all of the tested transactions were of full data integrity over 99.98% of transactions.

Distributed ledgers that are tamper proof and encryption standards that are used were able to secure high trust in handling freight data constituting to both the regulatory requirements and the business expectations. In this section, the proposed results are validated in that combination of AI, ML, IoT, and blockchain technologies has a potential as a scalable, efficient, and secure basis for modern transportation logistics.

The quantitative gains obtained through a route efficiency, cargo utilization, a system responsiveness metrics, as well as security respective metrics, affirm the potential transformation of the proposed system. In both logistics operations that are becoming more complex with more stringent customer expectations and in the transportation industry generally, such intelligent, data driven solutions will become indispensable in order to retain competitive advantage and perform well operationally.

IV. CONCLUSION

Dynamic routing and freight traceability based on integrating the AI/ML and Blockchain technologies is extremely important. It presents a dual framework; thus, it provides real time insights, reduces delivery delays, makes data integrity. With the distributed architecture, the scalability and adaptability is secured and the set up constitutes for a robust, future proof system for global logistics management in a dynamic changing transportation system.

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