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AN AI-BASED FRAMEWORK FOR ROUTE OPTIMIZATION IN LAST-MILE DELIVERY: IMPLICATIONS FOR E-COMMERCE LOGISTICS IN VIETNAM

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ABSTRACT

The explosive growth of e-commerce in Vietnam has significantly increased the need for last-mile delivery, which in turn has resulted in problems related to logistics efficiency, costs, and carbon emissions. In alignment with Vietnam's National Green Growth Strategy and the country's commitment to attain Net-zero emissions by 2050, the utilization of Artificial Intelligence (AI) for route optimization has become a strategic approach to improve delivery efficiency and cut down fuel consumption. This study examines how AI is currently being used for route optimization in Vietnam's e-commerce logistics sector and also introduces an AI-based model for last-mile delivery route optimization tailored to the specific context of emerging market like Vietnam, through the use of technologies such as Graph Machine Learning, Federated Learning, and Reinforcement Learning. This model aims to develop a more intelligent, efficient, and sustainable e-commerce logistics ecosystem in Vietnam. Moreover, this research provides practical implications for e-commerce logistics enterprises in Vietnam in adopting AI for route optimization in last-mile delivery.

Keywords: Artificial Intelligence (AI), Green logistics, Last-mile delivery, Route optimization, E-commerce, Vietnam.

1. INTRODUCTION

E-commerce has experienced a significant rise over the past few years and is considered one of the main components of global trade. The global e-commerce market is estimated to reach a value of approximately 6.15 trillion USD in 2023, according to the Avalara Report 2024 [1]. However, the explosive growth of e-commerce has not only led to a rapid increase in logistics activities, especially in the transportation sector, but also posed significant environmental challenges, especially issues related to emissions from logistics activities. In 2023, the World Economic Forum (WEF) reported that logistics sector is one of the leading causes of environmental pollution issues, being responsible for 11% of worldwide CO_2 emissions in 2023 [2]. Based on the 2023 report of Stand.earth Research Group projects that worldwide e-commerce will be able to deliver up to 800 billion packages/year by 2030, thereby releasing 100-160 million tons of CO_2 annually. This large amount of greenhouse gas emissions is equivalent to that of 44 coal-fired power plants in the US, assuming no changes in delivery methods and transportation fleet structure [3].

Last-mile delivery is often considered the most resource-intensive phase of the logistics supply chain, specifically in the e-commerce sector, because of increased complexity and higher density of deliveries in urban areas. Besides the fact that such an activity made up a significant percentage of the overall logistics costs, it is also one of the leading causes of large volumes of CO_2 emissions and fuel consumption. Research from Accenture in 2023 shows that last-mile delivery accounts for 53% of total transport costs and 41% of total supply chain costs. Consequently, carbon emissions from urban delivery traffic are expected to be 32% higher by 2030 if no measures are taken to counteract this trend [4].

In Vietnam, e-commerce has been growing rapidly, particularly since the COVID-19 pandemic, when demand for online shopping surged. The e-commerce sector has experienced remarkable growth, with the Vietnamese e-commerce market size reaching 32 billion USD in 2024 and an annual growth rate of 27%, according to the Vietnam E-commerce Association (VECOM) report [5]. The remarkable surge of e-commerce platforms, specifically Lazada, Shopee, and Tiki, has led to a substantial increase in demand for last-mile delivery. Although the growing demand for this service is clearly beneficial, it has also raised environmental concerns. Road transport maintains the leading position in usage compared to other modes of transport, accounting for 74.16% of the total freight volume carried in the first nine months of 2024 according to data from Vietnam Logistics Business Association [6]. However, it is also one of the primary contributors to CO_2 emissions and urban air pollution. In the cases of Ho Chi Minh City and Hanoi, which are densely populated cities, last-mile delivery is a major factor contributing to traffic congestion, resulting in the use of a larger amount of fuel and increased greenhouse gas emissions. Consequently, this poses a challenge to Vietnam's National Green Growth Strategy and the Global Sustainable Development Goals.

In that context, green logistics has become an inevitable trend to achieve the goal of sustainable development. Green logistics implements actions in order to reduce the emission of CO_2, the main contributor to environmental issues, by optimizing transport management and route planning, utilizing clean energy as well as promoting sustainable transport modes such as electric vehicles and autonomous vehicles [7], [8]. Previous studies demonstrate that the use of advanced technologies in delivery route management and optimization, as well as the adoption of green vehicles, is a crucial step in translating environmental commitments into practical actions [9], [10].

One of the emerging technologies supporting green logistics, Artificial Intelligence (AI), is regarded as a breakthrough tool, enabling the transition from traditional transport systems to more innovative and environmentally friendly modes of transportation. The use of AI in logistics to achieve route optimization, real-time traffic forecasting, and smart vehicle allocation, are a major step towards cutting down fuel consumption and CO_2 emissions in the supply chain [11]. The research paper of Hussain [12] state that AI-driven systems can accomplish on-time delivery rates of up to 98%, while significantly reducing fuel consumption through dynamic route planning.

There are two main approaches for solving route optimization. The first approach is to use the Salp Swarm Algorithm, a natural metaheuristic. This approach can help find the shortest, fastest, or lowest-cost path [13]. The second approach is to use Deep Reinforcement Learning (DRL), which defines route optimization as a sequential decision-making problem under the Markov Decision Process (MDP) framework. DRL discovers patterns that exceed handcrafted logic and facilitates rapid inference for time-sensitive, large-scale operations by learning through trial-and-error [14]. This paradigm is uniquely suited for real-world applications as it eliminates the need for expensive optimal labels and adapts to dynamic constraints [15].

Despite both SSA-based metaheuristics and DRL-based sequential decision-making models showing considerable potential for solving route optimization problems, their performance is heavily dependent on the characteristics of the operating environment [16] [17]. Prior research on AI-driven routing optimization has been primarily conducted in the structured urban environments of developed countries, characterized by standardized infrastructure and car-oriented traffic patterns [18], [19]. In contrast to developed countries, in emerging countries, last-mile delivery is usually hindered by heavy motorcycle congestion [20]. In large cities such as Hanoi and Ho Chi Minh City in Vietnam, motorcycles are the primary mode of transportation, clogging roadways and creating a "mixed traffic" where bikes, cars, and buses share narrow roads. This results in increased travel distances, fuel consumption, and carbon emissions for green logistics. There remains a significant need for algorithms tailored to high-density motorcycle saturation to meet the demands of urban centers in emerging markets like Vietnam.

There are structural issues in Vietnam's logistics sector that hinder the practical application of AI frameworks. Specifically, the absence of a centralized national data ecosystem due to a lack of coordination between government and private logistics firms creates barriers to implementing and scaling AI-driven optimization frameworks in practice [21] [22]. Under these circumstances, standard DRL architectures need to be modified to deploy. A viable solution for this problem is Federated Learning (FL), which shifts the data training environment from raw local data exchange to training on local edge devices (such as IoT sensors and regional servers) without requiring raw data exchange. By transmitting only anonymized mathematical parameters to a central hub, FL both ensures data privacy and facilitates a high-performance global model [23].

Furthermore, in Vietnam, the integration of AI to optimize last-mile delivery routes towards environmental goals remains minimal. The majority of Vietnamese e-commerce and logistics companies are in the early stages of digital transformation, and are still heavily dependent on traditional route-planning tools. In addition, e-commerce and logistics enterprises are concerned about investment costs, data mining capabilities, and the lack of technological human resources to deploy AI solutions effectively. As a result, despite great potential, the implementation is still mainly in the form of testing or discrete applications. This underscores the urgent need to research, evaluate, and propose an AI framework to optimize transportation routes, thereby improving operational efficiency and minimizing greenhouse gas emissions in the Vietnamese logistics and e-commerce sectors.

Therefore, this study aims at the following specific objectives:

1. Analyze the current status of AI applications in route optimization for last-mile delivery in the e-commerce logistics sector in Vietnam.

2. Propose an AI-based route optimization framework tailored for last-mile delivery in the e-commerce logistics sector in Vietnam.

3. Provide practical implications for e-commerce logistics enterprises in adopting AI for route optimization in last-mile delivery.

2. LITERATURE REVIEW

2.1. Green logistics

Green logistics refers to the initiatives that companies undertake to measure and mitigate the harmful environmental effects of their logistics operations [24]. Green logistics [25], involves not only the "greening" of transportation means but also the entire chain of operations, including warehousing, packaging, goods handling, and last-mile delivery. Whereas conventional logistics practices concentrate only on cost and time aspects, green logistics achieves not only economic efficiency but also environmental sustainability by reducing CO_2 emissions, optimizing energy use, and utilizing clean energy sources [26].

With the explosive growth of e-commerce, green logistics has been a necessary trend to reduce environmental harm and, at the same time, to raise the operational efficiency and sustainability of the e-commerce ecosystem. Delivery operations related to global e-commerce have the potential to produce over 800,000 tons of plastic waste and several hundreds of millions of tons of CO_2 by 2030 if proper measures are not taken [3]. This situation imposes on e-commerce companies the need to turn their logistics chains into "green" ones, which would also entail the use of recycled packaging materials, the delivery route optimization, and the employment of clean energy vehicles.

In [27] and [28], the implementation of green logistics is a key aspect of constructing a sustainable supply chain, which in turn leads to the reduction of emissions, saves resources and energy, and enhances international competitiveness. The adoption of green solutions, such as electric vehicles and route optimization, can reduce CO_2 emissions in urban logistics by up to 30%, thereby contributing to the achievement of the United Nations Sustainable Development Goals (SDGs), particularly goal 13 on climate action [29].

In the context of expanding e-commerce, green logistics has become an indispensable factor for businesses and countries to achieve their goal of Net-zero emissions and sustainable development. In the Asia-Pacific region, large enterprises such as Cainiao Network (China), Shopee Logistics (Singapore), or JD Logistics (China) have pioneered the application of technology to develop green logistics, proving the feasibility and benefits of this model in the e-commerce sector.

2.2. Last-mile delivery in E-commerce logistics

Last-mile delivery refers to a set of final activities in the delivery cycle, including a series of activities and processes carried out for the process of delivery from the last transit point to the final drop point of the delivery chain [30]. In other words, last-mile delivery is the final stage of the e-commerce supply chain, where goods are transported from the distribution center to the customer's doorstep [31]. It is the most costly and most emission-intensive stage in the e-commerce logistics chain. This stage accounts for approximately 53% of total logistics costs due to inefficiencies such as fragmented routing, lack of real-time tracking, and delivery failures [32]. Although last-mile delivery represents a relatively short distance, it accounts for up to 28% of total global transport-related carbon emissions [33]. This is mainly due to the use of fossil fuel-powered vehicles and the adoption of inefficient routes in congested traffic conditions. According to the study of Li [34] on the environmental impact of last-mile delivery, many failed deliveries, returns, and delays contribute to increased CO_2 emissions. In a developed market like Europe, where delivery bikes or micro-hubs are used as solutions to lessen the environmental impact, they still face challenges in terms of cost and scale. Hence, it is not only economically beneficial to optimize last-mile delivery but also to promote green logistics and environmental responsibility.

Last-mile delivery demand has experienced exponential growth due to the boom in global e-commerce, particularly following the COVID-19 pandemic. The worldwide last-mile delivery market was worth 166.45 billion U.S. dollars in 2024 and is projected to reach 311.31 billion U.S. dollars by 2031, with a compound annual growth rate (CAGR) of 9.62%. This growth is driven by the expansion of e-commerce, the increasing demand for faster deliveries, and advancements in technologies such as real-time tracking and autonomous vehicles [35]. Last-mile delivery, being the most intricate and costly phase of the supply chain, plays a crucial role in customer satisfaction. Hence, companies invest in route optimization and sustainable solutions. Proper handling of last-mile deliveries is a great way not only to improve the customer experience but also to reduce transportation costs, lower fuel emissions, and increase resource utilization [27].

Numerous recent studies have focused on proposing innovative solutions to enhance and optimize last-mile delivery, especially in the context of rapidly growing e-commerce, specifically highlighted the growing integration of cutting-edge technologies such as artificial intelligence (AI), machine learning, IoT, and big data in optimizing delivery processes [36], [37]. Combining route optimization algorithms with real-time tracking systems can lead to the reduction of delivery times and operational costs, and at the same time, improvement of customer satisfaction levels [38].

2.3. AI applications in route optimization

The issue of route optimization in supply chain networks has been widely discussed over the past few years. Route optimization for last-mile delivery is still a significant challenge because algorithms must address many multidimensional constraints simultaneously (i.e., volatile vehicle capacities, fluctuating energy consumption). Traditionally, this has been addressed through approximation or heuristic methods, including two-phase greedy heuristics [39], iterated tabu search [40], shuffled frog leaping [41], ant colony optimization [42], and genetic algorithms [43]. Although these handcrafted heuristics use domain expertise to produce rapid solutions for specific problem structures, they fail to generalize to slight changes in the inputs. They must be solved from scratch [44]. This lack of flexibility is problematic in emerging markets, where traffic and infrastructure are poorly aligned. Furthermore, routing optimization can be solved using the Salp Swarm Algorithm, a natural metaheuristic that finds the best possible route. While SSA is simple, flexible, and hybridizable, and performs well in complex optimization, it must be modified and combined with another method to scale up more effectively [16].

The rise of modern AI technologies such as Reinforcement Learning (RL), Graph Machine Learning, and Federated Learning has provided an efficient way to solve this problem [45], [46], [47]. The solutions provided by these technologies are also adaptable, extendable, and capable of change over time. As companies adopt these AI techniques, they can reduce costs, increase productivity, and enhance decision-making [48].

Reinforcement Learning (RL) has become an essential tool for enabling real-time, flexible decision-making in logistics. Essentially, these two types of RL approaches exist: model-based and model-free methods. Model-based RL endeavors to grasp a detailed model of the environment, including stochastic transitions and reward functions, and then uses it for planning. By contrast, model-free RL learns policies directly from experience through trial and error, without building a detailed internal model of the environment. Therefore, it effectively accommodates the changeable aspects of logistics in reality, where creating a flawless model that takes into account elements like traffic, weather, and unpredictable customer requirements is nearly unfeasible [49], [50].

Model-free approaches, such as Deep Q-Networks (DQN), operate by learning a direct mapping from states to optimal actions, thus allowing them to perform dynamic re-routing when faced with unexpected delays or cancellations. Proximal Policy Optimization (PPO) [51] is a policy gradient algorithm that enhances training stability by utilizing a clipped objective function. Due to its balance of sample, efficiency, ease of implementation, and firm performance, PPO is increasingly used to train agents to solve complex Vehicle Routing Problems (VRPs) autonomously [52]. In addition, Multi-Agent Reinforcement Learning (MARL) [53] extends this to more complicated situations involving multiple vehicles, such as a truck-drone system, where agents determine how to coordinate their routes not only to increase productivity but also to minimize the total operational cost.

Supply chains with their underlying network makeup are perfect candidates for Graph Machine Learning, in particular, Graph Neural Networks (GNNs). The complex and changing topologies of logistics networks are typically the primary reasons why traditional methods fail. On the other hand, this is a problem that GNNs can handle efficiently. GNNs work best for extracting features from network structures as this approach offers a deep understanding of the relationships between nodes, like warehouses, customers, and distribution centers [54].

The Graph Attention Network (GAT) [55] has emerged as a compelling architecture in recent years. Unlike standard Graph Neural Networks (GNNs), which treat all neighboring nodes as equally important, GATs utilize attention mechanisms to assign different weights to different nodes when gathering information. In a logistics network, GAT can learn that connections between two major hubs are more important than a local street serving a single customer. It assigns a higher attention weight when calculating the best path. This ability to identify and prioritize crucial connections leads to better routing decisions.

In recent years, as logistics networks have become more connected, emerging methods like Federated Learning [56] are gaining attention because they allow machine learning models to train on decentralized data sources without needing to store data in one place. This is useful in logistics, where data can be sensitive or spread across different partners in the supply chain. At the same time, multimodal deep reinforcement learning [57] is being combined with Internet of Things (IoT) technologies to build flexible and strong logistics networks. This method allows the system to process and learn from various data types, including sensor data, traffic reports, and weather forecasts. Then, it improves scheduling and strengthens global supply chains.

2.4. The current situation of applying AI to optimize transportation routes in e-commerce logistics sectors in Vietnam

Over the past decade, the logistics and e-commerce industry in Vietnam has experienced significant growth, accompanied by a wave of digital transformation. As a result, they have become the primary driving force of economic growth and international integration. Vietnam's transport and logistics market is expected to be worth 48.6 billion USD in 2024 and continue to grow to 71.9 billion USD in 2030 with a compound annual growth rate (CAGR) of 6.8% [58]. Domestic logistics companies have begun investing in digital technologies, including IoT, Big Data, Cloud Computing, and AI, to optimize costs and enhance their competitiveness. According to statistics from the Vietnam Logistics Business Association, about 50-60% of logistics enterprises have applied digital technologies in their operations [59].

According to the Vietnam E-commerce Association (VECOM), Vietnam's e-commerce market reached a scale of 32 billion USD in 2024, with a growth rate of 27% [60]. Large platforms like Shopee, Lazada, Tiki, and Sendo are driving demand for fast, flexible, and eco-friendly delivery. This puts a lot of pressure on the last-mile transportation system, which makes up approximately 53% of total logistics costs [33]. To tackle this problem, businesses have begun using digital technologies in their operations to improve delivery routes, shorten travel times, cut fuel use, and lower CO_2 emissions.

The Vietnamese Government has also issued policies to encourage green logistics in e-commerce and digital transformation such as the National Digital Transformation Program to 2025, with orientation to 2030 [61]; Decision No. 221/QD-TTg (2021) approving the "Action Plan for Green Logistics Development to 2030" [62]; National E-commerce Development Master Plan for the period 2026-2030 [63]. Thanks to that, the legal and technological environment is becoming favorable for the application of advanced technologies in logistics and e-commerce sectors in Vietnam. This Decision from the Government has encouraged businesses to apply AI, Big Data, and innovative technologies to transport management, route optimization, and demand forecasting, etc., to optimize the supply chain and reduce emissions, ultimately contributing to a green and sustainable logistics and e-commerce ecosystem.

In recent years, Vietnam has seen a major change in how digital technologies such as AI are applied in the e-commerce logistics sector. E-commerce logistics companies in Vietnam have started to use route optimization systems, which leverage AI and Big Data. However, the application of AI in route optimization is currently in its early stages of development, with a main focus on large enterprises or foreign-invested enterprises. For example, e-commerce companies such as Shopee Express, Giao Hang Nhanh (GHN), Viettel Post, and Ninja Van have begun using Machine Learning and optimization algorithms to suggest the shortest delivery routes, reduce empty miles, and optimize delivery times. Grab platforms have used AI algorithms to suggest the shortest routes, reducing fuel costs and delivery times, and integrating real-time traffic data to avoid congestion [64]. The application of breakthrough technology has helped reduce last-mile delivery costs by about 14% and increase the number of deliveries per vehicle by about 13% [65].

According to a survey by the Vietnam Logistics Business Association (VLA) published on the government website in 2024, approximately 52% of medium and large logistics enterprises have implemented Big Data & AI solutions in demand forecasting and route optimization [64]; however, most are still in the testing phase or integrating these solutions into a small part of their transportation operations. Additionally, with Vietnam's characteristics, such as high traffic density, a high proportion of motorbikes in urban areas, and an unsynchronized logistics infrastructure, these measures often fall short in achieving optimal performance. This raises an urgent need for developing an AI application for route optimization that is specifically designed to suit the context of emerging markets, such as Vietnam.

Although the National Green Growth Strategy encourages green logistics, Vietnam still lacks specific incentives, such as tax incentives or financial support, for businesses that apply AI and green vehicles. According to Mr. Bui Van Quy, Chairman of the ASEAN Seaports Association and Vice Chairman of the Vietnam Seaports Association, implementing the green transport program requires institutional, infrastructure, and human factors. The Government and State agencies need to have supportive regulations and policies to encourage businesses to transform digitally and adopt green practices [66]

The existing research on route optimization focuses on two main approaches, including the Salp Swarm Algorithm (SSA) and Deep Reinforcement Learning (DRL). SSA-based metaheuristic methods are popular because they are simple and adaptable, but they struggle with real-time navigation. Since routing involves discrete decisions and many constraints, SSA often requires substantial modifications to work in dynamic environments [16]. Its performance also tends to drop as the problem becomes more complex and involves a large number of constraints [16].

The biggest gap in current research is that most studies are built around well-structured, car-dominated road systems found in developed countries. These models are poorly suited for Vietnam's traffic reality, where motorbikes make up the majority of road users, and many streets are narrow and irregular. Additionally, since a majority of existing AI optimization frameworks rely on centralized databases, Vietnam's logistics sector suffers from a fragmented database, which results from minimal public-private coordination of data-sharing and the limitations imposed by Decree No. 13/2023/ND - CP, which places strict regulations on how sensitive and location-based data can be shared. Therefore, this research fills these gaps by introducing an application of AI for logistics route optimization that combines GAT (Graph Attention Networks), RL (Reinforcement Learning), and HFRL (Horizontal Federated Learning), targeting the distinct nature of Vietnam's roadways, data-sharing practices, and the national goals of green growth and data privacy as identified by the strategic directions articulated within existing national policies.

3. THE PROPOSED AI FRAMEWORK FOR DYNAMIC ROUTE OPTIMIZATION

Green logistics includes any practice that minimizes the environmental impact of the logistics network by reducing carbon emissions and fuel consumption. Conventional route optimization methods have difficulty because they rely heavily on centralized data collection. They increase privacy concerns when dealing with sensitive logistics data. Additionally, they struggle with scalability and real-time adaptability in large, distributed logistics networks, where data is often scattered among various parties, such as small companies or individual warehouses.

To address these issues, this paper presents a novel and decentralized framework for dynamic route optimization. This solution uses the Graph Attention Network (GAT) for state representation and Proximal Policy Optimization (PPO) for decision-making, all within a Horizontal Federated Reinforcement Learning (HFRL) setup.

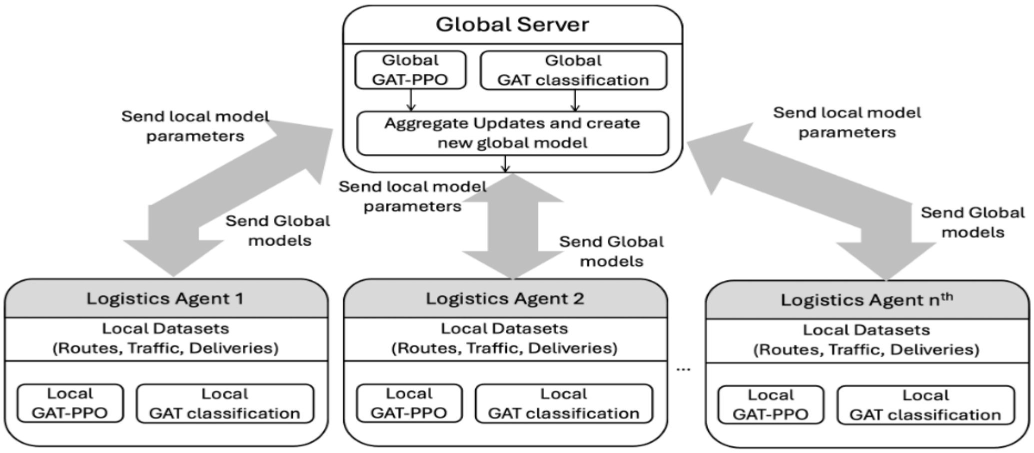

Figure 1. Proposed decentralized framework for dynamic route optimization

This method, illustrated in Figure 1, is designed for collaborative efforts. Instead of centralizing raw data, HFRL enables multiple logistics agents to collaborate in training a single, effective GAT-PPO policy. Agents share only their model updates (gradients) with a central server, keeping all sensitive, proprietary raw data safely stored. This method directly addresses the privacy and scalability issues associated with traditional approaches, enabling the industry to benefit from shared insights without compromising data security.

The proposed solution combines three following key components to solve the complex, dynamic problem of route optimization in green logistics:

3.1. Horizontal Federated Learning (HFRL)

Horizontal Federated Reinforcement Learning (HFRL) is a specialized distributed machine learning framework used when multiple datasets share the same feature space (i.e., identical data schemas, such as route data, traffic features, and delivery times) but come from different sources (i.e., distinct logistics agents or geographic regions).

The framework is important for green logistics in a distributed environment. Through HFRL, many logistics agents (i.e., small companies or warehouses) have the ability to train a strong, shared route optimization model jointly. Importantly, these agents only communicate model parameters (or updated weights), and never share their sensitive raw data (i.e., exact customer locations or delivery times). This decentralized approach can help to address the privacy concerns and scalability issues that are typically problems associated with centralized systems. In practice, this is how fleet vehicles can collaboratively adjust routes to reduce emissions by drawing insights from a large, varied dataset, while maintaining the independence and security of each company's confidential information.

Let $\{D_i\}_{i=1}^{N}$ be the local datasets of N agents, where each D_i has aligned features but unique samples. The global objective is to minimize a global loss function Eq. (1):

$$\theta^* = argmin_\theta \sum_{i=1}^{N} \frac{n_i}{n} F_i(\theta) \qquad (1)$$

where $F_i(\theta)$is the local loss (e.g., cross-entropy) on D_i, $n_i = | D_i |$is the number of samples, and $n = \sum n_i$is the total sample size.

The aggregator updates the global model $\theta_g$using weight averaging like Federated Averaging (FedAvg) Eq. (2):

$$\theta_g^{(t+1)} = \sum_{i=1}^{N} \frac{n_i}{n} \theta_i^{(t+1)} \qquad (2)$$

where $\theta_i^{(t+1)}$is the local model after t rounds of training.

3.2. Graph Attention Networks (GAT)

The Graph Attention Networks (GAT) algorithm is a neural network architecture engineered to learn sophisticated feature representations directly from network-structured data. Logistics networks, with their nodes (warehouses, delivery points) and edges (roads, routes), are naturally represented as a graph $G = (V, E)$, where $V$are nodes (e.g., warehouses, delivery points) and $E$are edges (e.g., roads with attributes like distance, traffic density, and emission factors).

GATs are essential for accurately modeling this complexity. In route optimization, the GAT's primary role is to create rich vector representations (embeddings) of the dynamic network state. It intelligently learns the relative importance of different nodes and edges (i.e., recognizing a severely congested route versus a clear one) based on dynamic features like real-time traffic or time-of-day. This superior data modeling provides a much richer and more accurate representation of the supply chain than traditional, simpler models. The GAT component has two important roles in the overall framework. First, it generates high-quality state representations for the RL algorithm to improve the route. Second, it classifies possible delivery delays, adding predictive insight to the optimization process.

The process of generate embeddings from GAT is descrbed as follow:

- Input: Node features $h_v \in R^F$for each node $v$in graph $G = (V, E)$, where $F$is the feature dimension, and edge features $e_{u,v}$(optional).
- Attention Mechanism: For layer l, compute attention coefficients using Eq. (3):

$$e_{u,v}^{(l)} = a\left(W^{(l)} h_u^{(l-1)}, W^{(l)} h_v^{(l-1)}, e_{u,v}\right) \qquad (3)$$

where $W^{(l)}$is a linear transformation matrix, and a is a single-layer feedforward neural network with LeakyReLU activation, which is defined using Eq. (4):

$$a(Wh_u, Wh_v) = LeakyReLU(a^T[Wh_u \,||\, Wh_v]) \qquad (4)$$

Here, || denotes concatenation, and $a$is a learnable attention vector.

- Normalized Attention: Apply softmax to obtain normalized coefficients Eq. (5):

$$\alpha_{u,v}^{(l)} = \frac{exp(e_{u,v}^{(l)})}{\sum_{k \in N(v)} exp(e_{k,v}^{(l)})} \qquad (5)$$

where $N(v)$is the set of neighbors of v.

- Update Rule: Aggregate neighbor features with attention weights Eq. (6):

$$h_v^{(l)} = \sigma\left(\sum_{u \in N(v)} \alpha_{u,v}^{(l)} W^{(l)} h_u^{(l-1)}\right) \quad (6)$$

where $\sigma$is a nonlinearity (e.g., ReLU).

Multi-Head Attention: To stabilize learning, use Kattention heads, concatenating or averaging their outputs Eq. (7):

$$h_v^{(l)} = ||_{k=1}^{K} \sigma\left(\sum_{u \in N(v)} \alpha_{u,v}^{k,(l)} W^{k,(l)} h_u^{(l-1)}\right) \quad (7)$$

3.3. Proximal Policy Optimization (PPO)

Proximal Policy Optimization (PPO) is an efficient and stable algorithm in reinforcement learning (RL). It serves as the main decision-making engine of our framework. It uses the rich data insights from the GAT embeddings to find the best policy. PPO is a policy-based, model-free algorithm that continuously learns the optimal routing policy to reduce the defined green logistics goals, such as minimizing delay, carbon emissions, and fuel use.

PPO's strength comes from its model-free approach. Unlike model-based methods that try to create an accurate environmental transition model, PPO focuses on improving the policy based on real-world rewards. This makes it stronger and more efficient in complex, changing logistics networks that face factors like variable traffic, weather, and road closures. PPO does not aim to model this chaos directly, which allows for quicker, real-time adjustments.

Using the RL approach, we can define the route optimization problem in logistics with the following components:

- State s_t: A graph embedding that captures the current position of the vehicle, the traffic situation, and some environmental factors like the weather, which is affecting the fuel consumption.
- Action a_t: A probabilistic selection of the following node or road segment that guarantees the maintenance of constraints, i.e., the load of the vehicle.
- Reward r_t: A multi-objective function, for example: $r_t = -\alpha \cdot emissions_t - \beta \cdot time_t + \gamma \cdot completion_t$, where emissions are calculated based on fuel use and green metrics.
- Transition $p(s_{t+1} \mid s_t, a_t)$: Stochastic due to real-time uncertainties like traffic variability.

PPO improves the AI's strategy for selecting actions from a specific state. However, it restricts how much the strategy can change at once to keep stability and trust. Its main objective is to estimate a policy $\pi(a_t \mid s_t)$, which maximizes the expected cumulative reward over episodes (delivery routes). The expected return $J(\theta)$is defined as Eq. (8):

$$J(\theta) = E_{s_t \sim \rho_{\pi_\theta}, a_t \sim \pi_\theta}[A^{\pi_\theta}(s_t, a_t)] \quad (8)$$

where ρ_{π_θ} is the stationary state distribution generated by π_θ, and $A^{\pi_\theta}(s_t, a_t)$is the advantage function. This function indicates by how much the action a_t is better than the average of the policy in state s_t. The optimization process employs gradients to alter the action probabilities of the policy. This stimulates the AI to select the least expensive routes more frequently.

To compute advantages, PPO uses Generalized Advantage Estimation (GAE) to reduce variance in temporal difference errors. The one-step temporal difference error is shown in Eq. (9):

$$\delta_t = r_t + \gamma V(s_{t+1}) - V(s_t) \qquad (9)$$

where $r_t$is the reward at time t, $\gamma \in [0,1]$ is the discount factor, which is most of the times set at 0.99, and $V(s_t)$ is the value function that approximates expected future rewards from s_t. The GAE advantage is shown in Eq. (10):

$$\hat{A}_t = \sum_{k=0}^{\infty} (\gamma\lambda)^k \delta_{t+k} \qquad (10)$$

where $\lambda \in [0,1]$ trades off bias and variance. This truncated sum gives a smooth estimate. It allows the agent to focus on long-term sustainability, such as cumulative emission reductions, instead of short-term gains.

In addition, PPO optimizes the policy using a clipped surrogate loss to enforce a trust region, limiting deviations from the data-collection policy $\pi_{\theta_{old}}$. The probability ratio is defined using Eq. (11):

$$r_t(\theta) = \frac{\pi_\theta(s_t)}{\pi_{\theta_{old}}(s_t)} \qquad (11)$$

The clipped objective is shown in Eq. (12):

$$L^{CLIP}(\theta) = \hat{E}_t\left[mi\left(r_t(\theta)\hat{A}_t, \backslash clip(r_t(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_t\right)\right] \qquad (12)$$

where $\hat{E}_t$is the empirical average over trajectories, and ϵ(e.g., 0.2) defines the clipping range. This formulation caps excessive updates, ensuring stable convergence in dynamic environments like logistics networks with variable traffic.

Total Loss Function

The complete loss integrates the clipped objective with value estimation and entropy regularization is shown in Eq. (13):

$$L(\theta) = \hat{E}_t[L^{CLIP}(\theta) - c_1 L^{VF}(\theta) + c_2 S[\pi_\theta](s_t)] \qquad (13)$$

where:

- The value function loss is defined using Eq. (14):

$$L^{VF}(\theta) = (V_\theta(s_t) - R_t)^2 \qquad (14)$$

with $R_t$as the target return (e.g., $r_t + \gamma V_\theta(s_{t+1})$) and c_1(e.g., 0.5) as a weighting coefficient.

- The entropy term is defined using Eq. (15):

$$S[\pi_\theta](s_t) = -\sum_a \pi_\theta(s_t)\, log\, log\, \pi_\theta(s_t) \qquad (15)$$

exploration with coefficient c_2(e.g., 0.01).

This multi-objective loss helps with balanced learning. Exploration supports the discovery of low-emission routes. PPO follows a step-by-step on-policy process:

1. Collect trajectories using $\pi_{\theta_{old}}$for a fixed horizon (e.g., 2048 steps).
2. Estimate advantages $\hat{A}_t$via GAE.
3. Optimize $L(\theta)$over multiple epochs (e.g., 10) with mini-batches (e.g., 64 samples), updating θvia gradient descent (e.g., Adam optimizer with learning rate 0.0003).

4. Update $\pi_{\theta_{old}}$to the new $\pi_\theta$and repeat.

3.4. GNN-based Delivery Delay Classification

Delivery delays are a major challenge in green logistics. They affect sustainability, such as causing higher idling emissions, and efficiency. In the solution shown in Figure 1, the node embeddings from GAT are reused to classify delays. It connects to a fully connected layer with softmax activation. This produces probability distributions over delay classes in Eq. (16), such as [on-time, minor delay, major delay].

$$P(v) = softmax\left(W_{out}h_v^{(L)} + b_{out}\right) \qquad (16)$$

where $W_{out}$and $b_{out}$are learnable parameters.

We propose a GNN-based classifier to predict probabilistic delays, integrating with the route optimizer for proactive rerouting.

The model is trained using cross-entropy loss for multi-class classification shown in Eq. (17):

$$L = -\frac{1}{|V|}\sum_{v\in V}\sum_{c=1}^{C} y_{v,c}\ \ log\ log\left(P(v)\right) \qquad (17)$$

where $y_{v,c}$is the ground-truth label (one-hot encoded) for class c (e.g., 0 for on-time, 1 for delay), and $C$is the number of classes. Regularization (e.g., L2) may be added to prevent overfitting.

4. DISCUSSION AND IMPLICATIONS

4.1. Discussion

4.1.1. The efficacy of GATs in modern route optimization

Since road networks are made up of intersections and roads, route optimization is basically a graph problem in which intersections are the nodes and roads connecting them are edges. Traditional methods usually treat locations as separate coordinates, which often misses how these places are actually connected. By contrast, Graph Neural Networks (GNNs) work on the graph structure directly, so they retain the network's topology, which is the specific relational configuration of how locations are linked [67]. This allows GNNs to distinguish between geographical proximity and actual accessibility, accounting for constraints such as one-way streets and natural barriers, such as river crossings. Graph Attention Networks (GATs) further enhance this capability by using a multi-head attention mechanism that automatically decides how much importance (weights) to give each neighboring node. This weighting adjusts in real time based on current conditions (i.e., changes in traffic or urgency of a delivery).

By utilizing an attention-based framework, GATs enable more flexible and expressive features to be inserted into the graph (e.g., traffic jams, road size, …). As a result, GATs allow for prioritizing critical paths and generalizing effectively across evolving urban landscapes. For example, when a GAT model is trained on local traffic data, it can learn to focus more on smaller roads or narrow alleys for motorbikes, even when the main roads nearby are jammed. As a result, it improves cost efficiency by reducing delivery time and operational costs. Also, it contributes to environmental sustainability by keeping vehicles within speed limits to reduce CO_2 emissions and avoid idle time in traffic jams.

4.1.2. Addressing limitation of GATs using Deep Reinforcement Learning Frameworks

The main limitation of GATs is computational cost, as their core component (the self-attention mechanism) must compute an attention coefficient for every edge in the graph to determine the best path [44]. As the network expands, it becomes a major problem because the calculations grow dramatically. To address this challenge, Deep Reinforcement Learning (DRL) can be integrated to shift the primary computational burden from the operational phase (inference) to the offline training phase. During training, the DRL model learns the underlying value of diverse graph connections through a trial-and-error process [17]. Once a DRL model is trained, it does not have to re-evaluate the entire map every time a new request comes in. Furthermore, DRL helps reduce search branches by automatically filtering out roads or areas that are not useful given current traffic conditions [17]. By focusing only on the most relevant parts of the network, this hybrid approach significantly accelerates inference. It can be a good fit for the dynamic, dense logistics environments in Vietnam

4.1.3. Horizontal Federated Learning

Horizontal Federated Learning (HFRL) is a collaborative training paradigm that enables multiple logistics enterprises to jointly develop a robust global AI model without centralizing their sensitive, proprietary datasets [23]. In green logistics, especially in highly competitive markets, companies are often reluctant to share their data, consisting of delivery records, customer locations, or internal bottlenecks, due to privacy laws and the need to protect business advantages. HFRL solves this by allowing each company to train its own model on its own server, then share only the model's parameters rather than the actual data. This keeps all raw data private and stored locally, while still allowing the combined global model to learn from the different routes and traffic patterns of all participants [23]. In this way, HFRL continues to improve route-optimization accuracy and to push the entire logistics industry toward more sustainable operations.

4.2. Implications

4.2.1. Theoretical Implications

The study contributes to the theoretical foundation of green logistics and AI applications in e-commerce. It introduces a contextualized AI model framework designed to optimize routes in last-mile delivery in emerging urban markets, specifically tailored to Vietnam's unique challenges, including high motorcycle density, frequent traffic congestion, and fragmented data. Additionally, this research offers empirical evidence from a developing market like Vietnam, where data infrastructure and AI human resources are limited. However, the potential for green e-commerce logistics development is substantial.

4.2.2. Practical Implications

4.2.2.1. For businesses in logistics and e-commerce industries

Companies might use AI-driven algorithms like Graph Machine Learning, Federated Learning, and Reinforcement Learning to make delivery routes more efficient, reduce the number of vehicles traveling empty, and save fuel. Besides that, the creation of a shared and collaborative logistics data platform plays a pivotal role in supporting AI training, interoperability, and real-time optimization.

4.2.2.2. For policymakers and regulators

Policy frameworks and regulations, along with incentives, should be established by the government in order to encourage enterprises to adopt AI-driven green logistics solutions. This might include tax benefits, financial support, innovation grants, especially for SMEs.

A key practical implication of this study is the creation of an open data platform to improve AI-based route optimization in Vietnam’s green logistics sector. This open data platform, supported by public-private partnerships (PPP), would allow for clear data sharing while keeping data private and secure. Besides, this platform is capable of integrating data from various sources such as e-commerce platforms, logistics companies, smart city traffic control systems, and environmental sensors. Creating real-time data sharing among the entities would help AI systems adjust routes dynamically to reduce delivery time, fuel usage, and carbon emissions.

These measures will accelerate Vietnam's implementation of the National Green Growth Strategy (2021–2030), aligning with the Master Plan for National E-Commerce Development for the period 2026–2030, Vietnam Logistics Development Strategy to 2030, and "Net Zero by 2050" commitment.

4.2.3. Social implications

The decrease in carbon dioxide emissions through route optimization for last-mile delivery will help improve air quality, particularly in big cities that are highly populated such as Ho Chi Minh City and Hanoi. Therefore, this will contribute to enhancing public health and overall quality of life. Moreover, this study acts as a guide for other emerging economies in ASEAN that deal with similar challenges from e-commerce and urbanization.

5. CONCLUSION

5.1. Conclusion

This study examined how artificial intelligence (AI) can enhance transportation routes to reduce CO_2 emissions and promote green logistics in Vietnam. The study offers a theoretical overview and assesses the current situation in Vietnam, affirming that artificial intelligence (AI) is a technological support tool that leads the way to transforming the entire supply chain, thereby raising efficiency and sustainability.

The utilization of AI in optimizing transportation routes can significantly reduce fuel costs, speed up delivery times, and enhance transportation planning accuracy, especially in last-mile delivery, which is the most energy-intensive part of e-commerce. This allows companies to reduce the negative effects of CO_2 emissions on the earth and comply with the ESG (Environmental, Social, Governance) standards in the international market. Moreover, the research pointed out that these companies in Vietnam face significant challenges such as unsynchronized data infrastructure, high costs of investments, and a shortage of qualified AI-related human resources. In order to effectively implement AI applications in green logistics, strong collaboration between the public and private sectors is essential. This is especially important for creating open data platforms, standardizing transportation information, and encouraging policies that support innovation in the logistics field.

5.2. Limitations

The study has developed a comprehensive AI framework, but it has several limitations that need to be addressed in future research. Firstly, the framework is still in the theoretical/architectural phase, so its impact on route optimization is currently only a projection and not supported by any large-scale simulation or real-world testing using Vietnamese traffic data. Secondly, for local logistics agents to use Federated Learning, they must have sufficient edge computing power to train their own GAT-PPO models. The majority of logistics companies in Vietnam are just beginning their digital transformation, and therefore, cost is a significant barrier to their adoption of the model. Finally, the AI framework does not accurately understand typical motorbike behavior in Vietnam, including frequent lane-splitting and using sidewalks when stuck in heavy traffic. Consequently, any AI-based predictions may not be accurate for all actual instances.

5.3. Future research

Future research should carry out empirical validation of the proposed framework to confirm that the system operates as predicted. Localized case studies across various wards in Ho Chi Minh City are necessary to lay the foundation for field-testing the proposed model. Preliminary data obtained through testing will facilitate iterative model refinement and ultimately enable the larger-scale deployment of the model in big cities like Hanoi and Ho Chi Minh City. In addition, strategic collaborations between Vietnamese e-commerce companies and last-mile delivery providers will need to be established to launch pilot programs. The use of Internet of Things (IoT) sensors to collect real-time data on vehicle performance and CO2 emissions would create an opportunity for researchers in both academia and industry to access high-quality datasets. Finally, further exploration of complex behaviors (such as lane splitting and navigating sidewalks) is essential for researchers adapting logistics frameworks to Vietnam's unique traffic conditions.

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