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Original Article

Dynamic Route Optimization for Trucks: Survey of Machine Learning-Based Techniques for Efficient Logistics and Transportation

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Abstract*: In the contemporary logistics and transportation infrastructure, dynamic optimization of truck routes is the key to achieving the highest efficiency, the reduction of costs, and ensuring timely delivery. Dynamic Vehicle Routing Problem (DVRP) reflects real-life uncertainties such as stochastic travel time, dynamic customer demands and changing availability of vehicles. In this paper, a detailed literature review of machine learning-based methods of dynamic route optimization in truck transportation systems. It surveys the unification of dissimilar data streams such as GPS positions, road surveillance systems, meteorological applications and Fleet management applications and highlights the significance of data preprocessing in a dependable model execution. Classical machine learning models like Support Vector Machines and Logistic Regression are presented and also advanced deep learning models like Long Short-Term Memory and Gated Recurrent Unit networks are discussed that are effective in capturing intricate spatiotemporal traffic behavior. The adaptive real-time decision-making is also discussed through reinforcement learning techniques namely Deep Q-Networks and policy-gradient approaches. According to the comparison performance results reported in recent works, deep learning-based routing frameworks can minimize average delivery time by more than 20%, increase on-time delivery rates by an average of 17% points, and reduce fuel consumption by up to 13% in comparison with traditional DVRP approaches. The survey also ends with the identification of the existing challenges and future research areas in terms of intelligent, scalable, and sustainable truck route optimization systems. Such results show how the ML-based approaches can be used to facilitate smart, scalable, and sustainable optimization of truck routes.*

Keywords*: Dynamic Vehicle Routing, Trucking Logistics, Machine Learning (ML), Route Optimization, Autonomous Trucks, Big Data Analytics, Transportation Efficiency.*

I. INTRODUCTION

The route planning is one of the most essential elements of the intelligent transportation system and has been extensively used in different areas such as daily travel and transportation to reduce costs, time and managerial expenses [1]. Road transport makes a crucial part of a network of global supply chains and the possibility that the transshipment of the good and the services can be performed in extremely long distances [2]. Nevertheless, a number of problems are associated with this means of transportation, including traffic congestions, probability of accidents and delays in optimization. Such problems are especially paramount in dynamic environments, like humanitarian logistics, where human lives are at stake because of timely and effective reaction. Insufficient up-to-date information on the road condition, road traffic conditions, and safety threats is one of the factors that worsen the situation of giving the logistics planners a guarantee to make informed decisions. Such overstretched road systems are not only causing traffic jam, but also fuel wastage which is worsening the environment. Accidents and crimes are some of the safety threats to the human being and the safety of the goods [3]. The issue of transport route optimisation is complicated by expenses, travel duration, traffic congestion, and safety hazards.

The optimization of international transportation systems is a burning topic that influences different industries, such as trade, humanitarian, and logistics [4]. There is the increasing need of an effective mode of transportation that is operationally and strategically demanding as the world turns into a global village. The process of transport optimization should include such factors as route planning, cost-efficiency, fuel consumption, and the unpredictability of the events that result in it e.g. natural calamities or political unrest. Late arrival of the humanitarian missions may also be a drastic incident because it can harm the personnel. It has to have a multi-criteria strategy that takes into account the latest technologies, including AI and machine learning, to optimize the paths and run with real-time data.

The AI and ML have become a strong tool to address the transport route optimization issues. Big data can be analyzed with the help of these technologies and new trends revealed which otherwise could not have been observed without technologies [5]. The aspect helps in saving on the time spent on traveling, using less fuel and it also reduces emissions and develops more sustainable transportation systems [6]. The machine learning issue may be a highly effective tool to address this problem because it is based on data-driven algorithms to optimize the load planning process, routing and demand prediction. The machine learning (ML) group has created a successful way of loading a truck. The different ML methods are able to handle large volumes of real-time data, and make informed decisions in real-time. The models are also able to forecast demand, dynamically divide space in trucks as well as optimizing routes depending on a number of conditions [7].

This survey addresses the opportunities of machine learning to transform truck loads optimization of retail logistics, outlines the new trends and discusses the obstacles that should be overcome to entirely realize the opportunities of these modern technologies. These gaps are the basis of the study as the research is going to offer an understanding of how logistics systems will evolve in the future under the impact of ML.

A. Organization of the Paper

The paper is structured in the following fashion: Section I presents the study, Section II describes the dynamic route optimization in trucking, Section III introduces machine learning-based VRP methods, Section IV discusses the route optimization of road transport, Section V is a review of the literature, and the last section, Section VI, is a conclusion of the paper.

II. DYNAMIC ROUTE OPTIMIZATION IN TRUCKING

The objective of stochastic transportation problem of the Dynamic Vehicle Routing Problem (DVRP) is to represent the behaviour of actual systems with an element of uncertainty and dynamism. Some of the real-life problems that are introduced in DVRP include dynamic arrival of the new customers, stochastic travel time and availability of the vehicles of events [8]. These elements bring the problem formulation closer to real-world logistics [9]. Customer availability changes are the most noticeable part of DVRP. Here are some ways to classify the dynamic parts of DVRP:

Dynamic consumers' Customer information is unveiled gradually and simultaneously with the execution of routes. In this category are requests that are subject to change, such as those involving location, demand, and availability.

- Dynamic order times: The customer delivery or service deadline might vary, and it might be necessary to fulfil it quicker than it was originally intended.
- Dynamic travel conditions: The arrival of a vehicle can be delayed by some external condition like traffic congestion or weather.
- Dynamic service times: The scheduled times of service or repair could vary according to circumstances at the customer location.
- Dynamic vehicle availability: The capacity and routing decisions of a fleet can be changed by unexpected events like vehicle breakdowns.

DVRP is strongly connected with simulation techniques because random changes of the environment should be modelled to mimic reality. The Discrete Event Simulation is ideal for use because transitions occur at specific time steps [10].

Recent studies highlight the challenges of integrating machine learning into DVRP. For instance, reinforcement-based methodologies that incorporate hybridization with metaheuristics (e.g., Simulated Annealing) enable the process of adapting to dynamic customer demands in real-time [11]. Equally, further extensions of tree-based search techniques, like Monte Carlo Tree Search (MCTS), to dynamic routing with stochastic events, like traffic jams, have been made. These algorithms model potential situations and update routes in an human like fashion and show encouraging advances over traditional static solutions and optimization algorithms.

A. Intermodal Truck Routing Problem (ITTRP)

The ITTRP arises in container ports with multiple terminals, necessitating the regular movement of containers between terminals, other yards, and facilities for logistics purposes. ITTRP is a specific facet of the classical VRP and is crucial for making ports more efficient, as well as reducing logistical costs and enhancing sustainability [12]. Optimizing solutions to the ITTRP related to these returns can be defined by the following objectives:

- Minimising delays associated with transport to maximise the flow of containers and avoid congestion.
- Minimising transport cost through truck use, distance travelled and time.
- Minimising empty trip costs by considering joint routings between trucking companies and/or load balancing.
- Minimising emissions associated with trucking by factoring emission costs into routing.

Several methodological strategies have been developed to address the ITTRP:

- The ITTRP is also a Mathematical Optimisation Model: Several optimisation models have been developed that minimise costs and delays subject to time-window and capacity requirements.

- Heuristic and Metaheuristic Algorithms: Various heuristics, such as greedy heuristics or metaheuristics, such as simulated annealing and hybrid approaches have been created to produce almost ideal results in a manageable computing time [13].
- Collaborative Routing Models: Any approach to relate the trucks (or trucking companies) collaboratively should lessen the number of empty trips or trip durations by sharing orders and resources.
- Multi objective Models: These models look to consider environmental factors, financial costs associated with vehicle costs, travel time, environmental penalties, and emissions into routing decisions.
- Technology-Based Solutions: Unique mobile applications that provide cloud-based platforms, monitor real-time tracking, and employ context-aware decision-making or suggest routing strategies [14].

A complicated issue because port operations are dynamic and stochastic, and the demand and traffic conditions of containers change constantly, and because coordination among actors in the supply chain systems is needed at a real-time scale [15]. Developing transport schedules and route optimisation, along with the introduction of intelligent decision-support systems, would be recommended as prospective study directions.

B. Self-Driving Trucks in Logistics

Self-driving trucks, also known as autonomous trucks, are profoundly changing how the logistics and transportation industries operate [16]. These trucks are equipped with cutting-edge artificial intelligence (AI), sensors, and autonomous operation capabilities, allowing them to operate without human oversight. Though autonomous trucks are initially aimed at the long-haul freight-related activities, a Real-time environmental identification can be facilitated by a mix of LiDAR sensors, cameras, radar, and other ultrasonic sensors [17]. Although LiDAR provides clear three-dimensional mapping for obstacle identification, cameras evaluate the status of traffic signals and lane markings, and AI algorithms facilitate decisions regarding vehicles' movements, navigation, and route planning in real-time. The artificial intelligence is essential to facilitate autonomy [18]. Machine learning algorithms make the trucks identify and react to road signs, improving their performance by what they have learned in their driving experiences through continuous learning.

The ability of self-driven trucks to immediately switch their direction to escape congested areas is a significant advantage as is the ability to process large amounts of data, including the condition of the road, the traffic and the weather and the road closures. This minimizes the delays and enhances the supply chain by enhancing fuel consumption and steady delivery performance [19][20]. Moreover, autonomous trucks do not need to be restricted by tiredness or controlled driving shifts as human drivers since they can work 24-hour days, as they are not fatigued. This boosts efficiency of the supply chain, minimizes delays and costs are further minimized.

C. Challenges and Potential Directions

In spite of this gigantic leap forward, many issues remain to be solved when it comes to using machine learning in retail logistics, especially in truckload optimization. The current challenges include some of the persistent challenges as:

- Data Quality and Availability: The accuracy of the ML model highly depends on real-time data availability and accuracy [21]. The performance of the model is affected by inconsistency and incomplete data.
- Scalability: Even though machine learning algorithms can be very effective in certain applications, the difficulty lies in the scaling of their capabilities to cover large and complex logistics networks [22].
- Real-time Adaptation: The model should be improved though most models achieve an efficient performance in steady environments, adjustment to the real-time logistics uncertainties [23], which includes sudden traffic changes and unexpected orders, are needed.
- Cost and Complexity: Implementing the ML models, in particular, deep learning and the hybrid models [24] is computationally expensive and needs trained staff.

III. MACHINE LEARNING-BASED TECHNIQUES AND ALGORITHM VRP

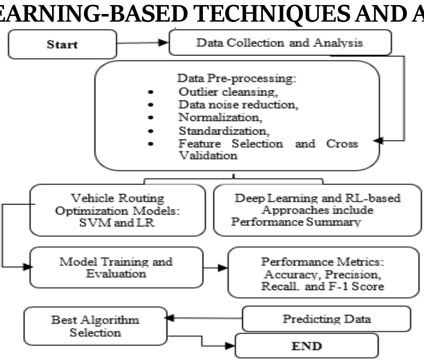

Figure 1 : Methodology Flowchart for the Research Approach

Logistics Transportation Route Optimization Algorithm enhances the efficiency of truckloads and optimization of delivery routes by addressing a Vehicle Routing Problem (VRP) using big data analytics and ML. The strategy addresses the major issues of data quality, scalability, and real-time flexibility, so that intelligent planning of routes based on the dynamic description is possible. The flowchart of the proposed method is shown in Figure 1 and it represents the general flow of the work in the optimization of VRP.

A. AI In Dynamic Route Planning for Transportation.

In the field of logistics AI has transformed the modern logistics system with the ability to create dynamic routes in transportation, enabling the use of data to make real-time decisions. The concept of route optimization is connected to the transportation management since it is a process of identifying the most effective routes to transport to reduce the delivery time, fuel consumption and cost or operating costs. Traditional techniques of manual planning and fixed route optimization do not consider dynamic variables in existence, which include traffic congestion, traffic uncertainty, weather changes, incidents and fuel prices. This has been transformed by AI and ML which takes advantage of real-time data feed provided by GPS systems and traffic sensors, weather APIs, and incident databases to constantly refresh and optimize the delivery routes [25]. The negations-driven systems are dynamic and responsive which allows the aspects of the logistics network to recalculate a change of course in real-time (based on a factor of disruption) and the waiting time is reduced, fuel savings are better, and operational efficiency is improved.

B. Data Collection and Analysis

The initial stage of any research data collection and analysis. This involve sorting the information in a file. It entails the following steps:

- GPS tracker, navigation systems, and transport agency traffic data also offer both real-time and historical information regarding congestion, road closures, and vehicle traffic.
- Meteorological services and APIs provide weather information, which is important in route planning (temperature, precipitation, visibility, and so on).
- Data on on-site logistics provided by fleet management systems delivers vehicle status, cargo, fuel consumption and turnaround times to facilitate effective routing and resource deployment.

The pre-processing stage process involved deletion of outliers, noise reduction, data normalization, data standardization, feature selection and cross-validation. The process was adopted to ensure the dataset was purged of inaccuracies and mistakes, the gaps in the dataset were managed adequately as well as the units were standardized [26]. All this resulted in enhanced quality, consistency and reliability of data and provided enough basis to effective optimization of dynamic routes in truck transport systems.

- Outlier Cleansing: The travel time, distance, and fuel consumption were outliers that were removed to produce optimal results of unrealistic optimization as well as realistic route modeling.
- Data Noise Reduction: The GPS and the traffic data were filtered with smoothing to remove random fluctuations and sensor errors in the data, which improved the accuracy of the input data.
- Normalization: These values of the feature were normalized to a normal range, which included distance, cost, and time, to achieve convergence of the model and prevent the tendency of the model to large values.
- Standardization: The data attributes were normalized such that the mean is zero and unit variance hence each variable contributed equally to the optimization program.
- Feature Selection: The features like the road conditions, the time windows in which the deliveries take place, and the traffic density were selected to enhance the effectiveness of the model and reduce the number of calculations.
- Cross-Validation: To assess the model's capacity for generalisation and reduce overfitting, the data was separated into training and validation sets, and offer reliable findings of the route optimization.

C. Vehicle Routing Optimization Models

Traditional techniques, which use both deterministic and non-deterministic methods, have been well investigated for classical vehicle routing problems (VRPs). In the logistics route planning domain, metaheuristic approaches such as Genetic Algorithms (GA), Simulated Annealing (SA), and Ant Colony Optimisation (ACO) algorithms, as well as the Travelling Salesman Problem (TSP) and the Clarke-Wright savings algorithm, have long been dominant. Although they are helpful in limited environment, these approaches are not good at real-time flexibility [27].

In recent years, Machine Learning and Predictive Models have introduced new models for traffic prediction and route optimization. Short-term prediction of traffic flow has been done using Support Vector Machines (SVMs), Random Forests (RFs), and ensemble. They however, perform poorly when faced with complicated temporal information.

a) Algorithms Selection

In pursuit of a refined road transport model, selected machine learning algorithms based on their track record of successfully resolving challenging optimisation issues and their capacity to handle massive amounts of data. The methods used are essential to achieving a high degree of accuracy in transport route prediction and optimisation. Each algorithm's breakdown and justifications are provided below.

i) Support Vector Machines (SVM)

SVMs are well known for their ability to solve high-dimensional classification problems, particularly when there are many dimensions involved. In route optimisation, where the association between input data (road conditions and traffic conditions) and the outcome (best routes) can be very non-linear, their capacity to represent non-linear decision boundaries using kernel methods delivers priceless applications.

- Strengths: SVMs are less likely to overfit and perform effectively in high-dimensional domains, especially when there are more dimensions than samples.
- Limitations: They require regularisation and a better kernel parameter selection, both of which can be expensive to optimise. Additionally, SVMs do not immediately provide probability estimates, which are crucial in some decision-making procedures.

ii) Logistic Regression (LR)

Logistic regression is a simple yet powerful model for binary problems, although it is not exhaustive. When implemented in the route optimization context, it can also make binary decisions, i.e., between 2 choices, selecting a route.

- Strengths: It is straightforward, easy to use and it also has the benefit of viewing the effect of every attribute.
- Limitations: It is limited to the orthogonal lines of the decision-making process that can impair its functioning in more complicated circumstances.

D. Deep Learning and RL-based Approaches

The emerging revolutionary technologies in route optimisation, deep learning and reinforcement learning (RL), provide astute, flexible, and data-driven solutions to complex transportation networks. Deep learning networks, particularly LSTM and GRU networks, are suitable for analysing long-term temporal relationships in time-series data, such as traffic movement, congestion behaviour, and vehicle movement patterns. Such models are superior to traditional statistical and ML approaches, as they practically approximate non-linear time-based associations, seasonal fluctuations, and situational dependencies in dynamic road conditions.

Deep Q-Networks (DQN), Policy Gradient-based techniques, and Reinforcement Learning (RL), in particular, have been deployed at the opposite end to make choices in uncertain environments. Another use of RL in the logistics field is the dynamic routing, adaptive scheduling and vehicle dispatch [28]. However, few studies integrate reinforcement-driven route modifications with real-time traffic forecasts inside a single framework. The practical potential of hybrid deep learning and RL techniques for intelligent transportation systems is highlighted by recent advances in integrating LSTM and Q-learning.

Table 1 displays a comparative performance summary of the suggested deep learning model and the conventional VRP, demonstrating gains in fuel usage, flexibility, average delivery time, and on-time delivery rate.

Table 1 : Comparative Performance Metrics of Traditional VRP and Proposed Deep Learning Model

Metric	Traditional VRP	Proposed Deep Model	Improvement
Average Delivery Time	52.4 min	41.2 min	21.3%
On-Time Delivery Rate	72%	89%	+17 pts
Fuel Consumption	6.8 L/100 km	5.9 L/100 km	13.2%
Adaptability Score	0.64	0.91	+42%

E. Model Training and Evaluation

The following indicators were employed to assess the results of the algorithm:

- Evaluate and rank using measures like AUC, F1-score, recall, precision, etc.
- A box plot is a useful tool for comparing the distribution of performance ratings among various algorithms.
- Problems in predicting correctly and incorrectly in a matrix.
- Generate separate sets of data for use in training, validation, and testing. Train the models on the training data and test them on the validation data.
- Utilize performance measures like load optimization accuracy, fuel usage, delivery time, and processing speed in an attempt to compare the models.
- To improve model performance and avoid overfitting or underfitting, adjust the hyperparameters.

IV. ROUTE OPTIMIZATION IN ROAD TRANSPORT

In order to increase the effectiveness, dependability, and profitability of logistics operations, road transport optimisation is crucial for cutting down on fuel consumption, journey time, and overall transportation expenses. For the most effective delivery across various forms of transportation, route optimisation generates route options using algorithms and other data-driven methodologies. Vehicle logistics multimodal route optimisation facilitates the transportation of automobiles by land, rail, or other means from production facilities to distribution hubs and dealerships, guaranteeing improved coordination, shorter wait times, and more equitable resource allocation [29]. In the meantime, the optimization of logistics transportation routes applies big data analytics and algorithms such as Tabu Search to enhance the multimodal transport planning, route assignment, and cost-efficiency [30]. These methods combined are the building blocks of road transport infrastructure, which allow logistics companies to seek out sustainable, intelligent, and profit-oriented transportation management.

A. Vehicle Logistics Intermodal Route Optimization.

Vehicle logistics is a vital component of the logistics system as a whole, and it deals with Transportation of automobiles to distribution facilities and then to dealerships. In a general sense, automobile logistics can be divided into parts logistics and vehicle logistics [31]. Parts logistics capture the flow of parts throughout the entire lifecycle, including procurement, production, sales as well as the recycling or import/export phases. Logistics for vehicles encompasses not only the transportation of parts but also waste, recycling, sales, import/export, and call-back services. Depending on the type of vehicle, sales logistics can be further categorized as either engineering, commercial, passenger, or special.

The optimal transportation system for maximizing profits is based on the topology of multimodal vehicle logistics networks. For this reason, constructing a strong and effective transportation network topology was required to achieve optimal route planning and maximum logistics efficiency.

B. Logistics Transportation Route Optimization.

Big Data Analysis and Logistics Transportation Route Optimisation Algorithm, was thoroughly examined in a range of transportation contexts to measure the degree to which operational efficiency within logistics can be improved. The experimental design was arranged to evaluate the performance of the algorithm, as well as its impact on several areas of transportation logistics, including route efficiency, reduced transportation costs, and resource efficiency.

The logistics transport routes of Company X were subjected to the Tabu Search Algorithm in order to provide data for optimisation study. The creation of a multimodal vehicle transport route with the goal of increasing overall logistics efficiency was the main focus of the optimisation. About 87% of Company X's whole route length was on roads, making road transport the primary component of their logistics network as opposed to railroads and waterways. In order to improve delivery performance and lower operating costs, the optimisation process aimed to create a more balanced and effective multimodal transport structure. The logistics transportation plan's optimisation outcomes are shown in Figures 2(a) and (b), which also show how the path proportions for various routes varied before and after optimisation. The optimised model successfully balances the usage of numerous transportation modes, eliminating excessive reliance on roads and increasing the use of rail transit, as shown by the comparison of highway and railway proportions in Figure 2 (a). The optimisation results for the identical routes are shown in Figure 2 (b) before and after, demonstrating a more reliable and effective allocation of transit routes after optimisation.

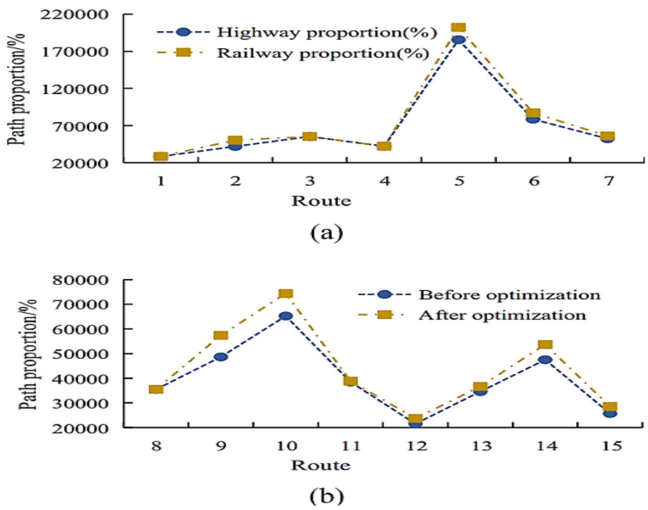

Figure 2 : (A) and (B) Optimization Results of the Transportation Plan for Profit Changes Before and After Optimization

The general tendency holds that the plan optimization would lead to the improved effectiveness of the route allocation, that would lead to the creation of a more balance multimodal transport system that would help in the added profit margins and operational efficiency of the logistics transportation.

C. Predictive Accuracy and Demand Forecasting

The deep learning models can make correct demand forecasting and conduct proactive route planning and load distribution to reduce the delays and operational bottlenecks. Anticipating changes in order volumes also allow logistics companies to flexibly distribute resources which enhance fleet optimization, fuel efficiency and on-time delivery.

- Demand Forecasting Accuracy: The implementation of DL models i.e. LSTM networks increased the accuracy of demand forecasting by 20% [32]. The better forecasting allowed the logistics company to plan better in high season, to predict fluctuations in quantity of orders and to redistribute the truckloads respectively.
- Optimization of Resource Utilization: The increased demand forecasting was beneficial in resource allocation, thus avoiding under-loading or over-loading of transport vehicles. Proper load balancing during peak times enhanced efficiency of operation, minimized costs, better fuel consumption, and delivery performance, customer satisfaction, and sustainability.

V. LITERATURE REVIEW

The existing literature review of dynamic vehicle routing combined with the areas of application of STs in logistics demonstrates the main tendencies, empirical findings, and technological innovations, which offer the key to guide the research and practical solutions in the future.

Chung's (2021) purpose is to assess all the significant advances related to the application of STs to improving the efficiency of the transportation system and logistics. The most crucial aspect is understanding the technical challenges academics face in implementing optimization strategies and examining how these challenges arise from ST applications. That completes the studies, and a recommendation for future study is also made. The emergence of smart technologies (STs) is causing significant changes in logistics and transportation. Through data science and artificial intelligence methods like machine learning and big data, STs use blockchain technology and the Internet of Things (IoT) to give things autonomy and cognitive awareness [33].

Yu et al. (2021) using the Internet of Things and cognitive algorithms to optimise transportation routes. To optimise GA, the coding mode, fitness function, selection, crossover, and mutation operators of the traditional GA are first examined. After environment the crossover probability and mutation probability to 0.6 and 0.1, respectively, the modified GA was utilised to develop a vehicle route optimisation model. Finally, simulations that optimised vehicle routes for fifteen client sites and a few distribution centres were used to assess the model's validity. Afterwards, distribution plans are determined using an algorithmic model that takes product demand and time sensitivity into account [34].

Dellermann, Gehring and Zirn (2020) Building a comprehensive optimum control plan based on anticipated powertrain data takes into account the statuses of the hybrid-electric drive train and electrified auxiliaries. An extra power network operating at 48 V supplies the powertrain and auxiliary equipment. The truck's total fuel consumption may be further decreased by maximising the energy transfer between the powertrain and auxiliaries. This contribution focuses on electrified auxiliaries, specifically air conditioners and air compressors. Numerous state-control combinations need to be tested. It makes use of heuristic knowledge to lessen computational effort. The driven path is divided into sections with a relatively consistent power demand to avoid manifestly irrelevant states [35].

Kucharska (2019) differentiates dynamic VRP, which considers the changing appearance of consumers to serve while designing or executing routes. Notably, the analysis accounts for both the known and the unpredictable components of the customer's availability. The algebraic-logical meta-model (ALMM) is first used to simulate the predicted variation in customers' availability based on a relevant general rule. This methodology allows for group decisions to be made at various points in the process, rather than for individual vehicles. A new algebraic-logical model is proposed to address the problem of dynamic vehicle routing with expected customer availability. This article shows how the ALMM method could be used to deal with changes in the environment, such as expected and unexpected client availability [36].

Nazari et al. (2018) developed a solitary model that, using only reward signals and feasibility rules, provides almost ideal answers for problem cases selected from a certain distribution. No need to retrain for each new problem instance, their trained model generates the answer as a series of sequential actions in real time, representing a parameterized stochastic policy that has been optimized using a policy gradient technique. For medium-sized instances on capacitated VRP, method achieves better solution quality than conventional heuristics and Google's OR-Tools, while consuming comparable amounts of computing time. In addition to the stochastic VRP and other VRP variants, their suggested framework could be used for combinatorial optimization issues in general [37].

Cattaruzza et al. (2017) explore the challenges encountered in urban areas while attempting to distribute vehicles efficiently. This methodology is utilized. For starters, it surveys the works written about optimizing routes for urban vehicles. It then sorts and examines logistic flows in cities. Therefore, it pinpoints the most pressing scientific issues that require fixing, including time-dependency, distribution organization with several levels and trips, and updated data. This paper ends by examining how the literature deals with each of these issues and with highlighting the underlying challenges they imply [38].

Table 2 gives a summary of the recent works, which summarizes their methods, main results, challenges and future suggestions to enhance the adoption and efficiency of dynamic vehicle routing to truck and smart technologies in logistics.

Table 2 : Literature Summary on Dynamic Route Optimization for Trucks.

Reference	Objectives	Methodology / Approach	Dataset / Application Domain	Key Findings / Contributions	Research Gaps
Chung (2021)	Identifying technical issues in optimization approaches and reviewing important contributions of Smart Technologies (STs) to increasing logistics operations and transport network efficiency.	Comprehensive literature review on AI, ML, IoT, and Blockchain integration in logistics and transport systems.	Secondary data from prior studies and industrial applications in logistics networks.	Highlighted that STs transform logistics through intelligent, data-driven optimization and automation.	The future studies are to consider how to incorporate the data in real-time between fields and evaluate ST-based optimization models at large scale because there is no empirical validation.
Yu et al. (2021)	To optimize vehicle routing using IoT and intelligent algorithms.	Improved Genetic Algorithm (GA) with refined fitness, selection, crossover (0.6), and mutation (0.1) parameters for vehicle routing.	Simulated data from distribution centers and 15 customer sites (IoT-based vehicle tracking environment).	Improved GA achieved higher efficiency and reduced delivery time, demonstrating the model's validity for route optimization.	Real-world IoT datasets not utilized; future work should integrate live sensor and traffic data for adaptive routing in dynamic environments.
Dellermann, et.al. (2020)	To design an optimal control strategy using predicted powertrain data for hybrid-electric trucks.	Developed an optimal control strategy using predictive modeling and heuristic evaluation to reduce computational load.	Powertrain data and simulation environment for hybrid-electric vehicles with electrified auxiliaries (air conditioners, compressors).	Reduced overall truck fuel consumption by optimizing energy flow between the powertrain and auxiliaries.	The lack of real-world testing is a limitation; future work could integrate predictive ML models for energy flow optimization and extend to electric fleets.
Kucharska (2019)	To distinguish dynamic VRP with predicted and unpredictable customer availability.	Proposed Algebraic-Logical Meta-Model (ALMM) for collective route decision-making across stages.	Synthetic dataset for dynamic customer availability scenarios.	Demonstrated ALMM's efficiency in handling dynamic VRP with predictive customer data, improving responsiveness.	Needs testing on large-scale, real-world logistics datasets; limited incorporation of external factors like traffic and weather.

Nazari et al. (2018)	This reinforcement learning-based model training aims to generate nearly optimal VRP solutions.	Policy gradient algorithm with stochastic policy representation; model learns through reward signals.	Capacitated VRP benchmark datasets (synthetic and standardized instances).	On medium-sized VRP instances, it outperformed classical heuristics and Google OR-Tools while requiring equivalent amounts of compute time.	Future research could generalize this model for stochastic, time-dependent, and dynamic VRPs; integration with real logistics data remains limited.
Cattaruzza et al. (2017)	To survey urban vehicle routing problems and identify main scientific challenges.	Systematic literature survey and classification of urban logistics optimization issues.	Review-based; focused on urban freight distribution problems.	Identified core challenges: time-dependency, dynamic routing, multi-level distribution, and real-time decision-making.	Highlighted need for dynamic, real-time, multi-modal route optimization frameworks integrating big data and AI-driven predictive analytics.

VI. CONCLUSION AND FUTURE WORK

This survey has discussed how machine learning has found application in dynamic optimization of truck transportation routes and that the old dynamic vehicle routing problem (DVRP) models are substituted by data-driven and adaptive optimization models. The modern logistic systems can adjust to the changes in the real-time traffic, weather, and the fluctuating demand slipping that lead to the drastic alteration of the delivery time, fuel usage, and operational elasticity, combining heterogeneous data sources and applying to the advanced learning models, such as the deep neural networks and the reinforcement learning. Despite this, in spite of these advancements, there exist several drawbacks including high levels of data dependency, high levels of computational complexity, reduced interpretability of deep models, and the challenges associated with the implementation of solutions based on learning to large-scale and real-life logistics networks that are defined by strong time and infrastructure constraints. Furthermore, the availability and quality of real-time data can also play a major role in the model robustness and reliability. The future work would be to develop hybrid optimization systems that combine explainable machine learning with the metaheuristic algorithm to scale up the former, explore distributed learning and edge models to optimize, encourage uncertainty sensitive and multi-objective optimization and empirically test the models with real-world industrial data. The challenges will be required to upgrade intelligent, reliable and sustainable route optimization solutions to next generation of transportation systems.

VII. REFERENCES

[1] Y. Geng et al., “Deep Reinforcement Learning Based Dynamic Route Planning for Minimizing Travel Time,” in 2021 IEEE International Conference on Communications Workshops (ICC Workshops), IEEE, Jun. 2021, pp. 1–6. doi: 10.1109/ICCWorkshops50388.2021.9473555.

[2] J. Thomas, K. V. Vedi, and S. Gupta, “The Effect and Challenges of the Internet of Things (IoT) on the Management of Supply Chains,” Int. J. Res. Anal. Rev., vol. 8, no. 3, 2021.

[3] S. S. Abosuliman and A. O. Almagrabi, “Routing and scheduling of intelligent autonomous vehicles in industrial logistics systems,” Soft Comput., vol. 25, no. 18, pp. 11975–11988, Sep. 2021, doi: 10.1007/s00500-021-05633-4.

[4] Q. Yan and Q. Zhang, “The Optimization of Transportation Costs in Logistics Enterprises with Time-Window Constraints,” Discret. Dyn. Nat. Soc., vol. 2015, pp. 1–10, 2015, doi: 10.1155/2015/365367.

[5] F. Zantalis, G. Koulouras, S. Karabetsos, and D. Kandris, “A Review of Machine Learning and IoT in Smart Transportation,” Futur. Internet, vol. 11, no. 4, p. 94, Apr. 2019, doi: 10.3390/fi11040094.

[6] S. K. Chintagunta and S. Amrale, “Enhancing Cloud Database Security Through Intelligent Threat Detection and Risk Mitigation,” Tech. Int. J. Eng. Res., vol. 9, no. 10, pp. 49–55, 2022, doi: 10.56975/tijer.v9i10.159996.

[7] A. Boukerche and J. Wang, “Machine Learning-based traffic prediction models for Intelligent Transportation Systems,” Comput. Networks, vol. 181, p. 107530, Nov. 2020, doi: 10.1016/j.comnet.2020.107530.

[8] V. M. L. G. Nerella, “Architecting Secure, Automated Multi-Cloud Database Platforms Strategies for Scalable Compliance.,” Int. J. Intell. Syst. Appl. Eng., vol. 9, pp. 128–138, 2021.

[9] M. Shahrier and A. Hasnat, “Route optimization issues and initiatives in Bangladesh: The context of regional significance,” Transp. Eng., vol. 4, Jun. 2021, doi: 10.1016/j.treng.2021.100054.

[10] V. Pillac, M. Gendreau, C. Guéret, and A. L. Medaglia, “A review of dynamic vehicle routing problems,” Eur. J. Oper. Res., vol. 225, no. 1, pp. 1–11, Feb. 2013, doi: 10.1016/j.ejor.2012.08.015.

[11] S. Thangavel, K. C. Sunkara, and S. Srinivasan, "Software-Defined Networking (SDN) in Cloud Data Centers: Optimizing Traffic Management for Hyper-Scale Infrastructure," Int. J. Emerg. Trends Comput. Sci. Inf. Technol., vol. 3, no. 1, pp. 29–42, 2022, doi: 10.63282/3050-9246.IJETCSIT-V3I3P104.

[12] T. N. Adi, H. Bae, and Y. A. Iskandar, "Interterminal Truck Routing Optimization Using Cooperative Multiagent Deep Reinforcement Learning," Processes, vol. 9, no. 10, p. 1728, Sep. 2021, doi: 10.3390/pr9101728.

[13] R. Tandon and D. Patel, "Evolution of Microservices Patterns for Designing HyperScalable Cloud-Native Architectures," ESP J. Eng. Technol. Adv., vol. 1, no. 1, pp. 288–297, 2021, doi: 10.56472/25832646/JETA-V1I1P131.

[14] G. Sarraf and V. Pal, "Privacy-Preserving Data Processing in Cloud : From Homomorphic Encryption to Federated Analytics," Int. J. Sci. Res. Comput. Sci. Eng. Inf. Technol., vol. 8, no. 2, pp. 735–706, 2022.

[15] T. N. Adi, Y. A. Iskandar, and H. Bae, "Interterminal Truck Routing Optimization Using Deep Reinforcement Learning," Sensors, vol. 20, no. 20, p. 5794, Oct. 2020, doi: 10.3390/s20205794.

[16] R. Patel, "A Survey on PLC Programming Languages and Their Applications in Modern Industrial Automation Industry," Int. J. Eng. Sci. Math., vol. 10, 2021.

[17] T. S. Combs, L. S. Sandt, M. P. Clamann, and N. C. McDonald, "Automated Vehicles and Pedestrian Safety: Exploring the Promise and Limits of Pedestrian Detection," Am. J. Prev. Med., vol. 56, no. 1, pp. 1–7, Jan. 2019, doi: 10.1016/j.amepre.2018.06.024.

[18] S. Garg, "Predictive Analytics and Auto Remediation using Artificial Inteligence and Machine learning in Cloud Computing Operations," Int. J. Innov. Res. Eng. Multidiscip. Phys. Sci., vol. 7, no. 2, 2019, doi: 10.5281/zenodo.15362327.

[19] A. A. Singh, A. K. M. K. Vishwakarma, M. G. Kawle, J. Satish, Badgujar, and D. K. C. Nalawade, "Reducing empty truck problem and route optimization for enhanced and sustainable logistic transportation," Int. J. Creat. Res. Thoughts, vol. 9, no. 6, 2021.

[20] V. Verma, "Big Data and Cloud Databases Revolutionizing Business Intelligence," TIJER, vol. 9, no. 1, pp. 48–58, 2022.

[21] K. Braekers, K. Ramaekers, and I. Van Nieuwenhuyse, "The vehicle routing problem: State of the art classification and review," Comput. Ind. Eng., vol. 99, pp. 300–313, Sep. 2016, doi: 10.1016/j.cie.2015.12.007.

[22] S. B. Venkata Naga, K. C. Sunkara, S. Thangavel, and R. Sundaram, "Secure and Scalable Data Replication Strategies in Distributed Storage Networks," Int. J. AI, BigData, Comput. Manag. Stud., vol. 2, no. 2, pp. 18–27, 2021, doi: 10.63282/3050-9416.IJAIBDCMS-V2I2P103.

[23] L. S. Iyer, "AI enabled applications towards intelligent transportation," Transp. Eng., vol. 5, Sep. 2021, doi: 10.1016/j.treng.2021.100083.

[24] R. Abduljabbar, H. Dia, S. Liyanage, and S. A. Bagloee, "Applications of Artificial Intelligence in Transport: An Overview," Sustainability, vol. 11, no. 1, p. 189, Jan. 2019, doi: 10.3390/su11010189.

[25] M. A. Rahman, A.-A. Hossain, B. Debnath, Z. M. Zefat, M. S. Morshed, and Z. H. Adnan, "Intelligent Vehicle Scheduling and Routing for a Chain of Retail Stores: A Case Study of Dhaka, Bangladesh," Logistics, vol. 5, no. 3, p. 63, Sep. 2021, doi: 10.3390/logistics5030063.

[26] S. Humagain, R. Sinha, E. Lai, and P. Ranjitkar, "A systematic review of route optimisation and pre-emption methods for emergency vehicles," Transp. Rev., vol. 40, no. 1, pp. 35–53, Jan. 2020, doi: 10.1080/01441647.2019.1649319.

[27] J. Thomas, K. V. Vedi, and S. Gupta, "Enhancing Supply Chain Resilience Through Cloud-Based SCM and Advanced Machine Learning: A Case Study of Logistics," J. Emerg. Technol. Innov. Res., vol. 8, no. 9, 2021.

[28] J. J. Q. Yu, W. Yu, and J. Gu, "Online Vehicle Routing With Neural Combinatorial Optimization and Deep Reinforcement Learning," IEEE Trans. Intell. Transp. Syst., vol. 20, no. 10, pp. 3806–3817, Oct. 2019, doi: 10.1109/TITS.2019.2909109.

[29] N. O. Alsrehin, A. F. Klaib, and A. Magableh, "Intelligent Transportation and Control Systems Using Data Mining and Machine Learning Techniques: A Comprehensive Study," IEEE Access, vol. 7, pp. 49830–49857, 2019, doi: 10.1109/ACCESS.2019.2909114.

[30] S. S. S. Neeli, "Serverless Databases: A Cost-Effective and Scalable Solution," Int. J. Innov. Res. Eng. Multidiscip. Phys. Sci., vol. 7, no. 6, p. 7, 2019.

[31] U. A. Korat, P. Yadav, and H. Shah, "An efficient hardware implementation of vector-based odd-even merge sorting," in 2017 IEEE 8th Annual Ubiquitous Computing, Electronics and Mobile Communication Conference (UEMCON), IEEE, Oct. 2017, pp. 654–657. doi: 10.1109/UEMCON.2017.8249010.

[32] Y. Lee, T. Ahn, C. Lee, S. Kim, and K. Park, "A Novel Path Planning Algorithm for Truck Platooning Using V2V Communication," Sensors, vol. 20, no. 24, p. 7022, Dec. 2020, doi: 10.3390/s20247022.

[33] S.-H. Chung, "Applications of smart technologies in logistics and transport: A review," Transp. Res. Part E Logist. Transp. Rev., vol. 153, p. 102455, Sep. 2021, doi: 10.1016/j.tre.2021.102455.

[34] Q. Yu et al., "Optimization of Vehicle Transportation Route Based on IoT," Math. Probl. Eng., vol. 2021, pp. 1–10, Sep. 2021, doi: 10.1155/2021/1312058.

[35] M. Dellermann, O. Gehring, and O. Zirn, "Optimal Control of a Multi Voltage Powernet with Electrified Auxiliaries in Hybrid-Electric Trucks," in 2020 IEEE International Conference on Environment and Electrical Engineering and 2020 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe), IEEE, Jun. 2020, pp. 1–6. doi: 10.1109/EEEIC/ICPSEurope49358.2020.9160600.

[36] E. Kucharska, "Dynamic Vehicle Routing Problem—Predictive and Unexpected Customer Availability," Symmetry (Basel)., vol. 11, no. 4, p. 546, Apr. 2019, doi: 10.3390/sym11040546.

[37] M. Nazari, A. Oroojlooy, L. V. Snyder, and M. Takáč, "Reinforcement Learning for Solving the Vehicle Routing Problem," Adv. Neural Inf. Process. Syst., vol. 2018-Decem, pp. 9839–9849, May 2018.

[38] D. Cattaruzza, N. Absi, D. Feillet, and J. González-Feliu, "Vehicle routing problems for city logistics," EURO J. Transp. Logist., vol. 6, no. 1, pp. 51–79, Mar. 2017, doi: 10.1007/s13676-014-0074-0.