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MACHINE LEARNING APPLICATIONS FOR DELIVERY TIME PREDICTION AND FREIGHT PLANNING

Nguyen Viet Hung, Trinh Thu Huong, Nguyen Tan, Truong Cong Doan, Nguyen Nam-Hoang **Machine Learning Applications for Delivery Time Prediction and Freight Planning.**

Abstract. The rapid advancement of technology has a profound impact on logistics and freight transportation. Efficient management of transportation schedules is vital for businesses seeking to minimize costs, reduce delivery delays, and improve customer satisfaction. One of the most important challenges in this field is the Vehicle Routing Problem with Time Windows (VRPTW), which requires not only finding optimal delivery routes but also adhering to specific timing constraints for each customer or delivery point. Traditional optimization methods often struggle with the complexity and dynamic nature of real-world logistics, particularly when dealing with large-scale datasets and unpredictable factors such as traffic congestion or weather conditions. To address these limitations, this study introduces a machine learning-based system that enhances the performance of existing VRPTW solutions. Unlike conventional approaches that rely solely on heuristics or static planning, our system employs modern machine learning models to predict key time-related parameters – including transit time, availability time, and service time – based on historical and contextual data. These predictive capabilities allow the routing algorithms to make more informed decisions, resulting in more accurate and adaptable scheduling. Building on previous research involving Random Forest models, we propose a more robust framework that incorporates advanced preprocessing techniques and feature engineering to improve model accuracy. By training and evaluating the system using real-world datasets, we are able to simulate practical scenarios and validate the effectiveness of our approach. Experimental results show that our proposed method consistently outperforms other commonly used machine learning models in terms of Mean Absolute Error (MAE), thus confirming its potential for real-world applications. Overall, this study contributes a scalable and intelligent solution to a longstanding logistics problem, paving the way for more responsive and cost-effective transportation systems.

Keywords: Vehicle Routing Problem with Time Windows (VRPTW), machine learning models, logistics optimization, transit time prediction, random forest improvement, data processing techniques.

1. Introduction. The transportation industry plays a pivotal role in the global supply chain, especially as the volume of freight movement continues to surge in response to rising consumer demand and evolving market expectations. With the rapid growth of e-commerce, same-day delivery services, and global trade expansion, transportation systems are under increasing pressure to operate with high levels of precision and reliability. This intensifying demand places a significant burden on logistics providers, who must now balance efficiency, cost-effectiveness, and punctuality while navigating various real-world constraints such as traffic congestion, driver availability, and unpredictable weather conditions. As a result, transportation companies are continuously seeking innovative solutions to maintain their competitive edge in a highly dynamic and time-sensitive environment.

Among the most pressing challenges is the ability to meet strict delivery time requirements – a factor that directly impacts customer satisfaction and loyalty. Inaccurate delivery estimates can lead to missed time windows, increased operational costs, and reputational damage. To address these concerns, predictive analytics and optimization techniques have become essential tools. Specifically, the Vehicle Routing Problem with Time Windows (VRPTW) has emerged as a critical area of focus within logistics and operations research. VRPTW involves not only determining the most efficient delivery routes but also ensuring that deliveries occur within specified time frames for each customer. Solving this problem effectively requires sophisticated algorithms and predictive models capable of handling complex constraints. Consequently, researchers and industry professionals are increasingly leveraging machine learning and data-driven approaches to improve the accuracy of delivery time predictions, optimize routing strategies, and ultimately enhance the overall performance of freight transportation systems [1–4].

The Vehicle Routing Problem with Time Windows (VRPTW) is a well-defined optimization framework aimed at identifying efficient delivery routes while adhering to both spatial and temporal constraints [4–6]. The spatial component of VRPTW involves calculating actual distances between delivery points using geographic coordinates such as latitude and longitude. In parallel, the temporal dimension encompasses constraints related to delivery time windows and customer availability, which must be carefully respected to maintain service reliability. Effective solutions to VRPTW are critical not only for minimizing delivery times but also for reducing operational costs, enhancing fleet and personnel utilization, and satisfying increasingly diverse customer demands.

Recent advancements in artificial intelligence, particularly in machine learning, have provided powerful tools to address the complexity of VRPTW. Deep learning architectures such as Convolutional Neural Networks (CNN), Long Short-Term Memory networks (LSTM), and Gated Recurrent Units (GRU) have proven effective in extracting temporal and spatial patterns from large-scale logistics data [7–9]. Additionally, ensemble-based models like Random Forest continue to be favored for their robustness and ability to handle heterogeneous data with high accuracy. These models are increasingly employed to predict critical time-related parameters – such as transport time, availability time, and service time – thereby enabling more accurate and adaptive route planning.

Despite their potential, the success of machine learning deployments in VRPTW heavily depends on the quality of the training data. Real-world logistics data are often noisy, incomplete, or inconsistently structured, which can hinder model performance if not properly addressed. Therefore, effective data preprocessing techniques – such as data cleaning, normalization, feature engineering, and outlier removal – are essential to improve both the reliability and accuracy of predictive models. Enhancing data quality not only improves computational outcomes but also strengthens the practical applicability of intelligent routing systems in dynamic operational environments.

In this study, we place strong emphasis on the role of data preprocessing as a foundational step toward constructing a high-quality training dataset that enhances the effectiveness of machine learning models. Recognizing the limitations of existing approaches, we introduce an improved framework built upon the Random Forest framework, which leverages the strengths of ensemble learning to deliver more robust and interpretable results. While deep learning models such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) architectures have shown great promise in various predictive tasks, our framework offers distinct advantages in terms of computational stability, efficiency, and the ability to handle high-dimensional and heterogeneous logistics data with minimal tuning.

The experimental evaluation of our framework reveals significant improvements in the accuracy of delivery time predictions, underscoring both its predictive power and its applicability in real-world scenarios. Through a systematic analysis of data preprocessing techniques – such as feature selection, normalization, and data cleaning – we demonstrate how enhancing dataset quality contributes directly to better model performance. Furthermore, by benchmarking our model against standard evaluation metrics and comparing it to existing machine learning approaches, we provide a comprehensive perspective on its practical advantages. Ultimately, this study presents a scalable and reliable solution to the Vehicle Routing Problem with Time Windows (VRPTW), contributing valuable insights to the ongoing efforts in logistics optimization within the modern transportation sector.

The remainder of this paper is organized as follows: Section 2 reviews related work on machine learning and optimization techniques for VRPTW. Section 3 presents the proposed methodology, including system design, data preprocessing, and feature construction. Section 4 describes the model training process and compares the proposed approach with various deep learning architectures. Section 5 provides a detailed performance evaluation of all models. Finally, Section 6 concludes the study and discusses future research directions.

2. Related work. The Vehicle Routing Problem with Time Windows (VRPTW) has been widely studied due to its practical importance in real-world logistics and transportation systems. Traditional approaches to solving VRPTW mainly rely on exact algorithms (e.g., branch-and-bound, branch-and-cut) and heuristics or metaheuristics such as Genetic Algorithms, Ant Colony Optimization, and Tabu Search [10–15]. While these methods are effective for small or medium-scale instances, they often struggle with scalability and adaptability in complex, real-time environments.

To address these limitations, recent research has increasingly focused on leveraging deep learning (DL) and machine learning (ML) models to enhance prediction capabilities and routing decisions under dynamic conditions. These models such as [7–9], particularly Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Gated Recurrent Units (GRUs), have shown promising results in capturing both spatial and temporal patterns in data, which are crucial for optimizing routes with strict time constraints.

CNNs are particularly useful for processing spatial information such as traffic density, road layout, and geographic coordinates. Studies such as [16–18], have demonstrated the effectiveness of CNNs in extracting relevant spatial features that influence routing outcomes. By transforming traffic data into grid-like representations, CNNs can identify local spatial patterns and support real-time decision-making in dynamic routing environments.

On the other hand, LSTM and GRU models have been widely applied to capture temporal dependencies inherent in sequential transportation data. These models are adept at modeling delivery schedules, vehicle movement sequences, and time-window constraints. For instance, [19, 20] show that LSTM networks significantly outperform traditional time-series models in predicting delivery time, availability windows, and service durations. The ability of LSTM and GRU to retain long-term dependencies makes them highly suitable for scenarios where previous routing decisions influence future performance.

Furthermore, hybrid architectures that combine CNNs for spatial representation and RNNs (LSTM/GRU) for temporal learning have gained popularity. These hybrid models benefit from the strengths of both types of networks and are particularly effective in multi-objective VRPTW problems, where factors such as delivery time, fuel consumption, and customer satisfaction must be balanced. For example, [21–24] integrate CNN and GRU in a single framework, achieving superior performance in both accuracy and generalization across diverse routing scenarios.

Another emerging direction in VRPTW research is the application of Deep Reinforcement Learning (DRL). Unlike supervised learning models that require labeled data, DRL models learn optimal routing strategies through interaction with an environment. Notably, DRL approaches using Pointer Networks and Transformer-based architectures have been proposed in [25–27] to tackle combinatorial optimization tasks, including VRPTW. These methods have shown strong potential in adapting to dynamic changes in demand and constraints by learning policies that generalize across problem instances.

Additionally, Graph Neural Networks (GNNs) are increasingly being employed to model the topological structure of road networks. Since road networks naturally form graphs, GNNs offer a more intuitive and effective representation compared to grid-based or sequential models. Research in [7, 28–30] has shown that GNNs, when combined with temporal models like LSTM or CNN [31, 32], significantly improve performance in routing tasks by incorporating both spatial connectivity and historical behavior.

Overall, the integration of deep learning models in solving VRPTW not only enhances prediction accuracy but also supports scalable and adaptive route planning systems. However, challenges remain in terms of model interpretability, real-time deployment, and generalization to unseen environments. Future work may focus on combining different deep learning paradigms (e.g., DRL with GNNs), incorporating domain knowledge through constraint-aware learning, and leveraging transfer learning to improve model robustness in varying logistical contexts.

3. Proposed Method

3.1. System Overview. This section presents the overall system architecture developed for delivery time prediction and freight planning based on the VRPTW framework. The proposed system consists of three main components: data preprocessing, model training, and route optimization. The workflow begins with transforming raw logistics data into structured input features, followed by training machine learning models to predict key delivery time parameters. These predictions are then integrated into route optimization algorithms to support effective decision-making. An overview of the system pipeline is illustrated in Figure 1.

The system consists of three main components:

– **Data Preprocessing**. The first step involves extracting and structuring VRPTW (Vehicle Routing Problem with Time Windows) data to create a training-ready dataset. This includes collecting data on customer locations, delivery time windows, vehicle capacities, and distances. The data is cleaned, normalized, and features are extracted, such as travel times, cluster analysis of delivery points, and distance metrics. This structured dataset serves as the foundation for training machine learning models.

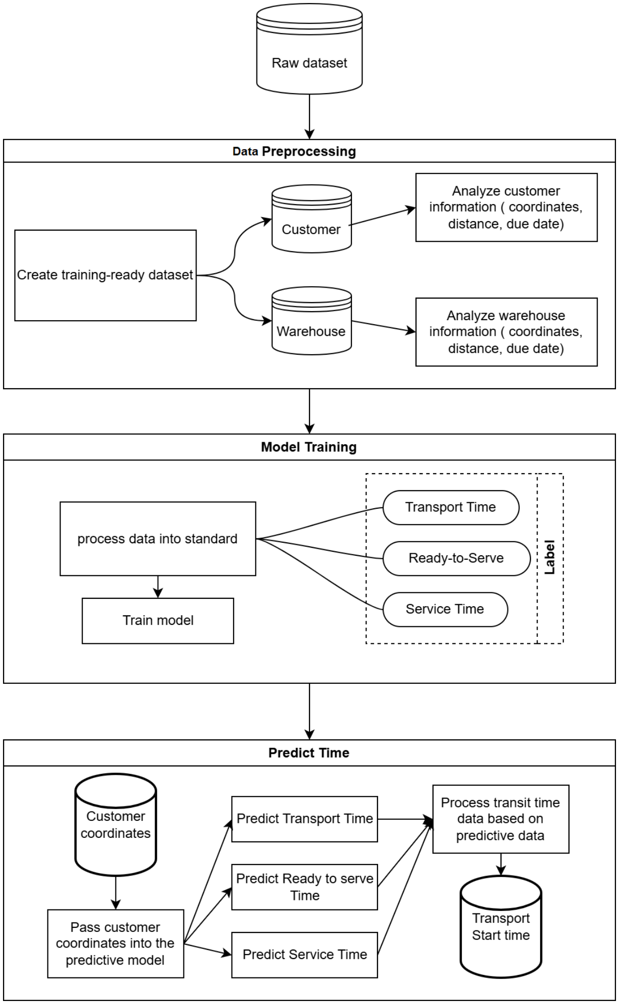


Fig. 1. Proposed System Architecture and Implementation Framework

– **Model Training**. In this phase, multiple machine learning models are trained to predict time metrics and optimize routes. Models include CNN (for spatial relationships), LSTM and GRU (for time-series predictions), and a proposed custom model designed for VRPTW optimization. The models are trained on the preprocessed dataset, with hyperparameter tuning and performance evaluation using metrics like accuracy and mean absolute error (MAE). The goal is to identify the most effective model for real-world applications.

– **Route Optimization and Prediction**. Trained models are applied to optimize delivery routes and predict time metrics using real-world data. The system integrates machine learning predictions with classical optimization algorithms (e.g., Dijkstra, Genetic Algorithm) to calculate the shortest or most efficient routes while respecting constraints like time windows and vehicle capacities. The models also predict travel times based on real-time traffic and road conditions. Results are evaluated against actual delivery performance to ensure accuracy and reliability.

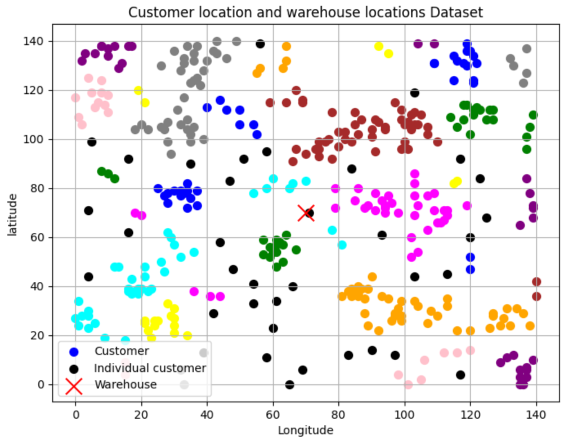
3.2. Building and Development Model

3.2.1. Data Source and Preprocessing. This research utilizes the **VRPTW Homberger dataset**, which includes instances with 100, 200, and 400 customers. It can be publicly accessed from: [33–35] Each instance contains three main components: **warehouse data**, which provides the spatial coordinates (x, y) of a single warehouse; **customer data**, which includes each customer's identifier, location (a, b), demand, ready time, expiration time, and service time; and **vehicle data**, which specifies the number of vehicles and their maximum load capacity. To prepare the dataset for model training, we developed a **Data Preprocessing Module** to systematically extract, clean, and organize the data. This ensures the training data is reliable, minimizes potential risks, and improves the efficiency of downstream tasks.

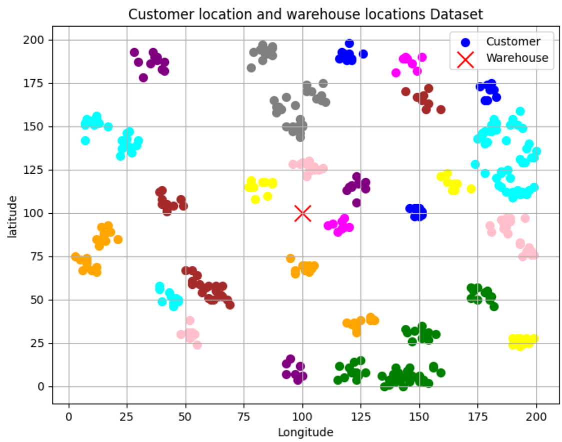
On the one hand, the preprocessing process begins with a detailed exploration of the dataset, which is categorized into three scales based on the number of customers: 100, 200, and 400. This classification allows the model to handle a variety of scenarios, from simple to complex. A thorough analysis confirms that the dataset provides all necessary information for computing input features, thereby reducing the risk of bias and improving data consistency. The next step involves extracting and organizing the data into three categories: **warehouse data**, which is duplicated to match the number of customers in each instance (e.g., repeated 400 times for a 400-customer dataset to facilitate pairwise calculations); **customer data**, which includes attributes such as demand, time windows, and location; and **vehicle data**, which specifies the number and capacity of vehicles.

On the other hand, Figures 2(a, b) illustrate the distribution of customer locations and warehouse sites within two distinct datasets.

In Figure 2(a), various colors represent individual customers, while the red cross marks the optimal warehouse location. The customer data points are scattered across a range of latitudes and longitudes, highlighting the geographic spread of customers.



a)



b)

Fig. 2. An example of clustering customers and optimal warehouse locations: a) customer and warehouse location distribution – Dataset 1 (200 Customers); b) customer and warehouse location distribution – Dataset 2 (400 Customers)

Figure 2(b) presents a similar analysis but features a different dataset, showcasing varying clusters of customers with the optimal warehouse location again indicated by the red cross. Both visualizations provide insights into customer distribution patterns, which are essential for optimizing warehouse placement and improving logistics efficiency.

However, the central warehouse location was fixed in these examples for visualization purposes only. Although the warehouse appears centrally located, this does not represent an optimized warehouse position, nor does it assume uniform customer distribution. In fact, customer locations in these datasets are non-uniform, with varying densities and clustering patterns. These figures are intended to demonstrate spatial diversity and emphasize the model's ability to adapt to different geographic layouts. During training, the machine learning model does not rely on spatial centrality and is designed to generalize across varied logistical scenarios.

Finally, the extracted data is restructured into a **list of dictionaries**, where each dictionary represents a complete dataset. This structure separates the warehouse data (repeated for each customer) and customer data (containing detailed customer information), ensuring consistency and simplifying the definition of model inputs and outputs. By following this systematic approach, the data is prepared in a reliable and structured manner, ready to support efficient and flexible model training.

3.2.2. Feature Construction and Label Calculation. Upon completing the data preprocessing process, the next step involves the construction of features and the calculation of labels to create a structured input dataset suitable for training the machine learning model. These features and labels are derived based on the spatial, temporal, and operational constraints of the VRPTW problem.

The feature extraction process begins by pairing the coordinates of the warehouse and each customer to determine the spatial relationship between them. The Euclidean distance [36] between the warehouse and each customer is calculated using the formula proposed by Solomon [37], shown below:

$$D_i = \sqrt{(X_i - X_k)^2 + (Y_i - Y_k)^2}, \tag{1}$$

where:

– D_i – Euclidean distance (in kilometers) between the warehouse and customer i.

– X_i, Y_i – Coordinates of customer i.

– X_k, Y_k – Coordinates of the warehouse.

In addition to the spatial features, temporal features play a critical role in capturing service constraints. Each customer's time window, defined by the ready time (T_s) and expiration time (T_h), is included as part of the temporal features. The final feature set consists of the warehouse coordinates (X_k, Y_k), customer coordinates (X_i, Y_i), the distance (D_i), and the expiration time (T_h).

To simulate real-world operations, the label calculation process is performed concurrently with feature construction. The transportation time (T_v) from the warehouse to the customer is computed based on the Euclidean distance (D_i) and an assumed vehicle speed of 80 km/h. The transit time is converted to minutes using the following formula:

$$T_v = \frac{D_i}{80} \cdot 60, \tag{2}$$

where:

– T_v – Transit time (in minutes).
– D_i – Distance (in kilometers).

The availability time of each customer is adjusted to ensure compliance with operational constraints. Specifically, the adjusted service availability time (T_{sp}) is calculated by comparing the initial ready time (T_s) with a minimum threshold of 390 minutes (corresponding to 6:30 AM):

$$T_{sp} = \max{(T_s, 390)}, \tag{3}$$

where:

– T_{sp} – Adjusted service availability time (in minutes).
– T_s – Initial ready time.

The service time at the customer location is then determined based on the difference between the expiration time (T_h) and the adjusted availability time (T_{sp}), with a maximum service time limit of 90 minutes to reflect operational constraints:

$$T_p = \min{(T_h - T_{sp}, 90)}, \tag{4}$$

where:

– T_p – Service time (in minutes).
– T_h – Expiration time.
– T_{sp} – Adjusted service availability time.

After calculating features and labels, the dataset is thoroughly cleaned to ensure data quality. Records with invalid values, such as negative transit times or service times, are removed. This cleaning step eliminates inconsistencies and ensures all features and labels are valid and realistic.

The cleaned data is then organized into a structured data table, where features and labels are compiled and ready for further processing. To prevent potential order bias, the dataset is randomly shuffled before being split into training and testing sets, with 80% used for training and 20% for testing. Finally, all input features are normalized to the range $[0, 1]$ to enhance the training performance of the machine learning model.

It is important to note that the use of Euclidean distance in this study is a simplifying assumption. The VRPTW Homberger dataset does not provide road network data or graph-based routing information. As such, the calculated distance between the warehouse and each customer is based on direct linear distance (as per Solomon's formula [34]). This does not account for actual driving routes, road curvature, traffic constraints, or urban infrastructure. While this approach allows consistent feature engineering within the constraints of the dataset, we acknowledge it limits real-world accuracy. We have addressed this limitation in the conclusion and recommend future extensions to incorporate road network data or graph-based shortest path algorithms.

3.2.3. Pre-training Dataset. For a Homberger instance with 400 customers, the pre-training dataset is structured as follows:

– **Total Records**. The dataset contains a total of 400 records, with each record corresponding to an individual customer.

– **Features**. Each record includes 6 feature dimensions:
– Warehouse coordinates (X_k, Y_k).
– Customer coordinates (X_i, Y_i).
– Euclidean distance (D_i) between the warehouse and the customer.
– Customer expiration time (T_h).
– **Labels**. Each record is associated with 3 label dimensions:
– Transportation time (T_v).
– Adjusted service availability time (T_{sp}).
– Service time (T_p).
– **Dataset Splitting**.
– **Training Set**. Consists of 320 records (80% of the dataset).
– **Test Set**. Comprises 80 records (20% of the dataset).

The dataset was manually split into 80% training and 20% testing by the authors. Prior to splitting, the data was randomly shuffled to minimize order bias and ensure generalizability. The structured dataset is saved in a reusable format, enabling further analysis and experimentation. This organization ensures the dataset can be efficiently integrated into machine learning workflows while maintaining consistency and traceability for future use.

3.2.4. Preprocessed Data Analysis. The preprocessed dataset was analyzed to evaluate the feature distribution, label characteristics, and overall data quality, ensuring its suitability for training machine learning models.

Feature Distribution. The Euclidean distances exhibit high variability, reflecting the diverse geographic distribution of customers in the Homberger dataset. To prevent this variability from biasing model training, normalization was applied to scale the distances to a consistent range.

In addition, in the competitive landscape of logistics and transportation, accurately predicting delivery times is essential for optimizing operations and enhancing customer satisfaction. To achieve this, several key features must be considered during the modeling process. These features provide valuable insights into the factors that influence transportation efficiency and service delivery. Below, we delve into three critical label features that play a pivotal role in our predictive models:

– **Transit Time:** strongly correlated with the Euclidean distance, transit time provides a clear and predictable signal, making it an important feature for learning models.

– **Service Availability Time:** typically adjusted to a lower bound of 390 minutes (6:30 AM), this label captures operational constraints that models need to account for during prediction.

– **Service Time:** highly variable and capped at a maximum of 90 minutes, service time is the most challenging metric to predict due to its dependence on customer-specific constraints.

Data Quality. Preprocessing ensures that the dataset contains no missing or invalid values. The shuffling step effectively minimizes any order-related biases that may have been present in the original VRPTW files, thereby enhancing the randomness and robustness of the dataset.

Conclusion. This rigorous preprocessing and analysis process produces a high-quality dataset that is well-suited for training machine learning models. The standardized format and balanced feature-label representation ensure effective and unbiased model learning.

4. Model Training and Proposed Framework

4.1. The Importance of Predictive Labels. In this part, we focus on predicting three key delivery time-related labels, including:

Transit Time (T_v). This is the time it takes for a vehicle to travel from the warehouse to the customer, calculated based on the distance and speed of the vehicle. This label is important because it directly affects the total delivery time and the ability to plan routes efficiently. Accurately predicting the transit time helps ensure that vehicles arrive on time, avoiding violations of customer time windows.

Ready to Serve Time (T_sp). This is the time when the customer is ready to receive the goods, adjusted to ensure that it is consistent with operational reality (minimum 390 minutes, corresponding to 6:30 AM). This label plays an important role in customer service sequencing, ensuring that vehicles arrive at the right time for customers to pick up their goods, thereby optimizing delivery schedules and reducing waiting times.

Service Time (T_p). This is the time required to deliver goods and complete related tasks at the customer's location, limited to a maximum of 90 minutes. Accurate prediction of service time helps ensure that the total dwell time at each customer does not exceed the allowed time window, and also supports planning so that vehicles can continue their route without delay.

Accurate prediction of these three labels is the foundation for optimizing delivery routes in the VRPTW problem. The above labels not only help to minimize operating costs but also improve customer satisfaction through on-time delivery. Therefore, selecting the appropriate machine learning model to predict these labels is an important task, requiring careful consideration between accuracy, generalizability, and computational efficiency.

4.2. Description and Reason for Choosing CNN, LSTM, GRU Models for Comparison. To evaluate the performance of the proposed model, we choose three popular deep learning models: Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU). These models are chosen because they represent state-of-the-art deep learning methods, are capable of handling complex data types and problems, and are widely used in time prediction research. Below is a detailed description and rationale for choosing each model:

4.2.1. Convolutional Neural Network (CNN). CNN is a type of deep learning neural network commonly used to process spatially structured data, such as images in [7]. In our research, we designed a CNN with 3 convolutional layers (Conv2D) with 32, 64, and 128 filters, combined with batch normalization layers to stabilize the training process, a max-pooling layer to reduce the feature dimension, and dense layers with 256, 128, and 3 neurons to make the final prediction. The input data is reformatted into a square image (e.g., 3x3x1) to match the CNN architecture.

We chose CNN because of its outstanding ability to extract spatial patterns from the data. Although the VRPTW data is largely tabular, reformatting the data into images allows the CNN to exploit spatial relationships between features such as warehouse coordinates, customer coordinates, and distances. CNNs are typically effective in prediction problems based on spatially structured data, so they are a strong candidate for comparison with the proposed model to assess whether sophisticated deep learning methods can outperform traditional methods in this problem.

4.2.2. Long Short-Term Memory (LSTM). LSTM [8] is a variant of a recurrent neural network (RNN), designed to process sequence data and has the ability to remember information over long time periods thanks to the gate mechanism. In our research, LSTM consists of 2 LSTM layers with 128 and 64 units, in which the first layer has a return sequences parameter (with the value True) to return the output sequence, combined with a dense layer (32 and 3 neurons) to predict three labels. The input data is reformatted into a sequence with 1 time step and 6 features to match the LSTM architecture.

LSTM is chosen because of its ability to handle temporal relationships, which may exist in VRPTW data through features such as ready time and expiration time. Although VRPTW data is not purely a time series, reformatting the data into a sequence allows LSTM to exploit latent time-related patterns. LSTM is commonly used in delivery time prediction or scheduling problems due to its ability to learn long-term dependencies, so it is a suitable model for comparison, to test whether sequence-based deep learning methods can provide an advantage over the proposed model.

However, we recognize that our implementation uses only a single time step per sample, which prevents the model from learning any true temporal dependencies. Additionally, in our PyTorch implementation, the hidden state is reset at the beginning of each batch, meaning that memory from previous sequences is not retained. As such, this model is not expected to outperform simpler architectures in this context, but was included to test the behavior of gated memory units when applied to static inputs.

4.2.3. Gated Recurrent Units (GRU). GRU [9] is another variant of RNN, similar to LSTM but simpler by using fewer gates (update and reset gates). The GRU model in this research consists of 2 GRU layers, each with 64 units, with the first layer having the `return_sequences` parameter set to `True`, combined with batch normalization and dense layers (128 and 3 neurons) to make predictions. The input data is also formatted as a sequence similar to LSTM.

We chose GRU because it is a lighter version of LSTM, providing higher computational efficiency while maintaining the ability to learn temporal dependencies. GRU is often used in problems that require sequence processing but require faster training speed than LSTM, such as time prediction in logistics. Comparing GRU with the proposed model helps to evaluate whether a lighter deep learning model can compete with the traditional method, and also provides a comprehensive view of the performance of deep learning methods on this problem.

As with LSTM, the GRU in this study processes only one time step per sample. Because the hidden state is reinitialized at each batch, the network cannot benefit from sequence memory. This limits the ability of GRU to learn meaningful temporal patterns in our setup, but allows us to evaluate its effectiveness when applied to tabular data through a sequence-like structure.

4.3. Advantages of our framework and Model Structure Comparison. Our proposal can be called Delivery Time Prediction – Machine Learning (DTP-ML).

Description. Our framework is a Random Forest-based model [38], an ensemble learning method that uses multiple training iterations to make predictions. The DTP-ML model is designed with 90–100 training iterations (the optimal range determined by the experiment shown in Table 1), the input data is tabular data with 6 features and does not require data reformatting. We have taken advantage of the voting mechanism of training iterations to increase accuracy and reduce overfitting.

Table 1. Model structures, inputs, and computational requirements

Model	**Main Structure**	**Input**	**Number of Main Layers**	**Tuning Parameters**	**Computational Requirements**
CNN	3 Conv2D layers (32, 64, 128 filters), MaxPooling, Dense (256, 128, 3)	Square Image (3x3x1)	3 convolutional layers, 3 dense layers	Learning rate (0.001), dropout rate (0.001), number of filters	High (requires GPU)
LSTM	2 LSTM layers (128, 64 units), Dense (32, 3)	Chain (1 time step, 6 features)	2 LSTM layers, 2 dense layers	Learning rate (0.001), dropout rate (0.001), number of units	Very High (requires GPU)
GRU	2 GRU layers (64 units), Dense (128, 3)	Chain (1 time step, 6 features)	2 GRU layers, 2 dense layers	Learning rate (0.001), dropout rate (0.001), number of units	High (requires GPU)
DTP-ML	Training batch (90–100 trainings)	Panel data (6 features)	Multiple training	Number of training runs (90–100)	Low (no GPU required)

4.3.1. Advantages compared to CNN, LSTM, GRU. Suitable for Tabular Data [39]: VRPTW data is tabular, and the proposed model has directly processed this data without reformatting, avoiding noise or information loss as in CNN (must be formatted into images) or LSTM/GRU (must be formatted into sequences). This allows the DTP-ML model to exploit the maximum information from features such as distance and coordinates.

4.3.2. Stability and Generalization. We applied an ensemble learning mechanism to DTP-ML, combining predictions from multiple training runs to reduce overfitting. Meanwhile, deep learning models such as CNN, LSTM, and GRU are prone to overfitting if not carefully tuned (e.g. needing a dropout rate of 0.001 and stopping early), especially with small or unstructured data.

4.3.3. Computational Efficiency. Our proposed model has a significantly faster training time than deep learning models, which require GPU resources and many iterations (150 rounds). With 90–100 training runs, DTP-ML achieves high accuracy without the need for powerful hardware, suitable for real-time applications in logistics.

4.3.4. Easy Tuning. DTP-ML only requires tuning the number of training iterations (90–100 is optimal), while CNN, LSTM, and GRU require tuning many parameters such as learning rate, dropout rate, number of layers, and number of units in each layer. This simplicity makes the model easier to deploy in real-world scenarios and easier to maintain.

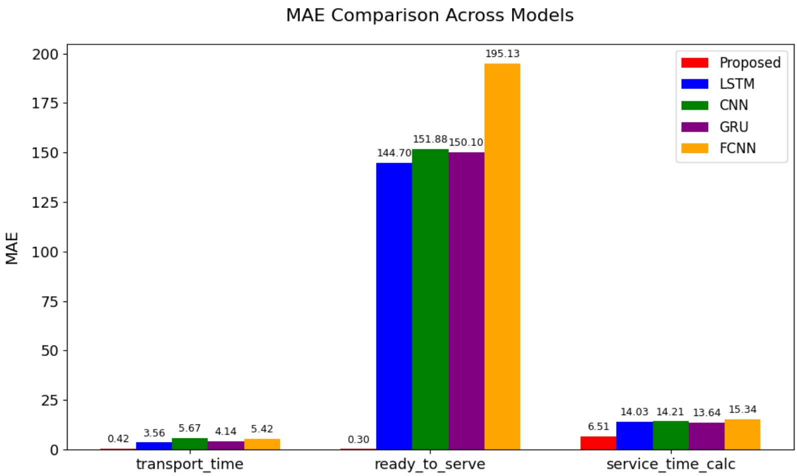
On the other hand, we can see that in Table 1 shows that DTP-ML has a simpler structure, does not require complex data block reformatting, and has significantly lower computational requirements than CNN, LSTM, and GRU. This highlights the superiority of the proposed model in predicting delivery time, especially in the context of the VRPTW problem with structured table data.

While our proposed model leverages ensemble learning for tabular data, we recognize that other architectures designed specifically for tabular regression problems – such as FT-Transformer [40] and GLN [41] – offer promising directions. These models are capable of modeling non-linear interactions in high-dimensional data with strong regularization. Although not implemented in this study due to computational constraints, we propose incorporating these architectures in future work to further benchmark our solution.

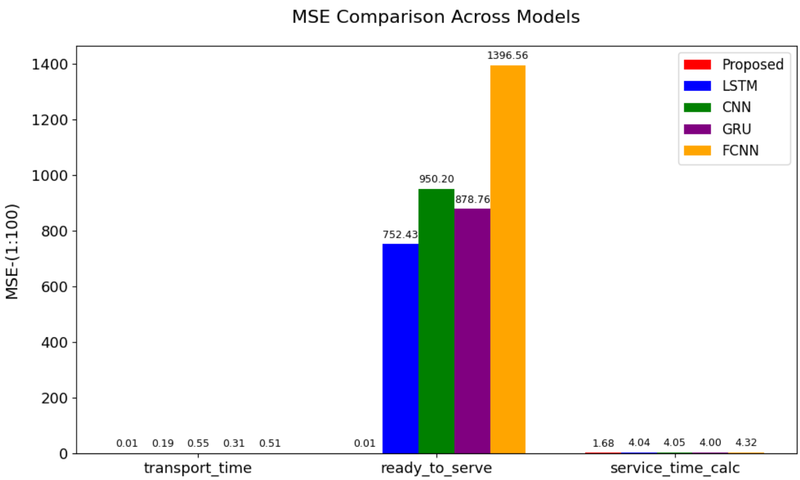
We also acknowledge that a two-layer fully connected neural network (FCNN) is a relevant and commonly used baseline for tabular regression problems. We plan to include this model in future extensions of our research to further enrich the performance comparison and establish more representative benchmarks.

5. Performance Evaluation

5.1. Training performance. Figure 3 and Figure 4 shows the performance of all models on the test set, using the metrics Mean Absolute Error (MAE) in the formula 5, Mean Squared Error (MSE) in the formula 6, Coefficient of Determination (R^2) in the formula (7), and Accuracy (relative error $< 10\%$) in the formula (8).

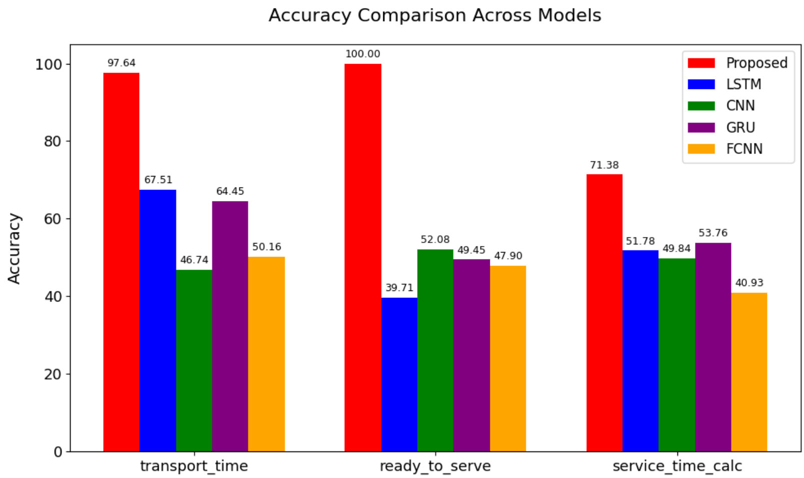


a)

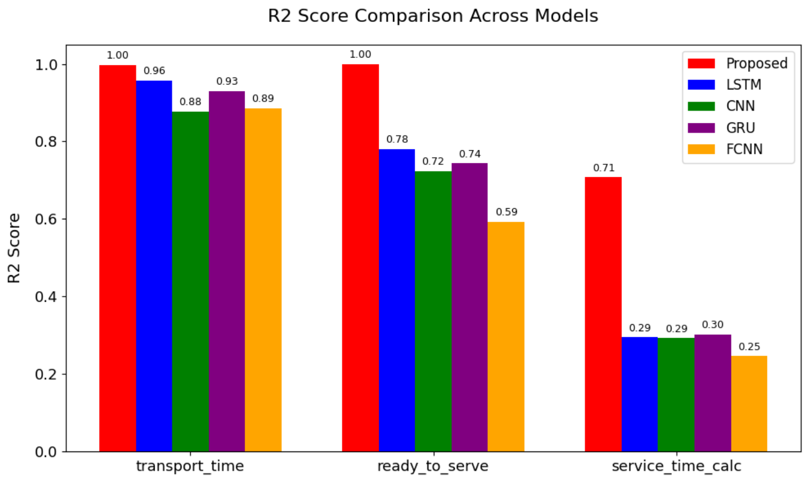


b)

Fig. 3. Error Metric Comparison (MAE and MSE) of machine learning models for delivery time prediction: a) mean Absolute Error (MAE) of different models on delivery time features; b) mean Squared Error (MSE) comparison among models



a)



b)

Fig. 4. Accuracy and R² score comparison of machine learning models for delivery time prediction: a) accuracy comparison of proposed, LSTM, CNN, and GRU models on delivery time features; b) R^2 Score evaluation of all models across delivery time features

On the one hand, before evaluating the model's performance, the following metrics were used to quantitatively assess the prediction results:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i^{label} - \hat{y}_i^{label}\right|, \tag{5}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i^{label} - \hat{y}_i^{label}\right)^2, \tag{6}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i^{label} - \hat{y}_i^{label}\right)^2}{\sum_{i=1}^{n}\left(y_i^{label} - \bar{y}^{label}\right)^2}, \tag{7}$$

$$Accuracy = \left(\frac{\sum_{i=1}^{n}\mathbb{I}\left(\frac{|y_i^{label} - \hat{y}_i^{label}|}{y_i^{label}} < 0.1\right)}{n}\right) \times 100\%. \tag{8}$$

In the formulas above:

– y_i^{label} represents the true value of the target variable for sample i. In this research, the target variables are: Transport time, Ready to serve, or Service time.

– $\hat{y}_i^{label}$ denotes the predicted value generated by the model for sample i.

– $\mathbb{I}(\cdot)$ is the indicator function, which returns 1 if the condition inside is true (i.e., the relative error between the predicted value and the true value is less than 10%), and returns 0 otherwise.

On the other hand, the **Transport Time Prediction** that in the task of predicting transport time, the DTP-ML model achieved the best performance with a Mean Absolute Error (MAE) of 0.4203, outperforming the LSTM model, which recorded a slightly higher MAE of 0.6659. This indicates the superior precision of DTP-ML in modeling this task. In contrast, CNN and GRU exhibited significantly poorer performance, with MAE values of 2.7542 and 2.9459, respectively. In terms of accuracy, DTP-ML achieved a high score of 97.64%, reinforcing its effectiveness in this task.

In addition, the **Ready-to-Serve Time Prediction** for the ready-to-serve time task, both DTP-ML and LSTM models reached perfect prediction accuracy (100%) and R^2 scores of 1.0000, suggesting an excellent fit to the data.

However, DTP-ML clearly outperformed LSTM in terms of error magnitude, achieving a much lower MAE of 0.3031 compared to LSTM's 1.4463. On the other hand, CNN and GRU exhibited substantially higher MAE values of 15.0827 and 13.4415, respectively. Although their R^2 values remained high, this is likely due to the constrained distribution of the labels rather than true predictive accuracy.

Finally, the **Service Time Prediction**, in the most challenging task – service time prediction – DTP-ML once again demonstrated its superiority. It achieved an MAE of 8.5142 and an R^2 of 0.7075, which are significantly better than those of the other models. LSTM, CNN, and GRU showed much higher MAE values (14.9116, 15.6824, and 15.8123, respectively) and correspondingly low R^2 scores (ranging from 0.1206 to 0.2066), indicating weaker model fit. DTP-ML also attained the highest prediction accuracy for this task, with a score of 71.38%, whereas all other models recorded accuracy rates below 46%.

5.2. Effect of Training Times in DTP-ML. Table 2 presents the accuracy (in percentage) of the DTP-ML model across three tasks – Transport Time, Ready-to-Serve Time, and Service Time – under varying numbers of training iterations, ranging from 50 to 150. To better understand the model's performance stability and trends across these tasks, a detailed analysis and evaluation are conducted based on the results shown in the table.

Table 2. Accuracy for different numbers of experimental training

No. of Times	Transport Times (%)	Ready-to-Serve Times (%)	Service Times (%)
50	97.67	82.62	81.68
60	97.67	82.92	81.68
70	97.72	83.02	81.77
80	97.73	82.85	81.63
90	97.76	82.74	81.65
100	97.88	82.63	81.74
110	97.76	82.62	81.85
120	97.84	82.72	81.67
130	97.75	82.71	81.65
140	97.78	82.69	81.65
150	97.82	82.75	81.65

5.2.1. Delivery Time. Accuracy increases gradually from 97.67% (50 training runs) to a peak of 97.88% (100 training runs), and then fluctuates slightly between 97.75–97.84% as the number of training runs increases to 150. This shows that the performance of DTP-ML on this task peaks at 100 training runs and stabilizes thereafter, confirming that around 90–100 training runs is the optimal choice to achieve high accuracy without increasing computational complexity.

5.2.2. Ready to Serve Time. Accuracy fluctuates between 82.62–83.02%, with the highest value achieved at 70 training runs (83.02%). However, after 70 training runs, the accuracy drops slightly and fluctuates around 82.62–82.75%. This may reflect that higher training runs do not provide a significant benefit for this task, and a model with 70–100 training runs is sufficient to achieve good performance. Although the accuracy in this table is lower than the 100% recorded in Table 1, this may be due to factors such as the way the accuracy is calculated or the different test datasets.

5.2.3. Service Time. Accuracy ranges from 81.63% to 81.85%, with the highest value achieved at 110 training runs (81.85%). However, the improvement between training runs is very small, and the accuracy stabilizes around 81.65–81.85% from 90 training runs onwards. This suggests that the performance of DTP-ML for this task also reaches a steady state around 90–100 training runs, similar to other tasks.

5.2.4. Overall Comments. Based on the accuracy table, DTP-ML shows stable and peak performance with training runs from 90 to 100 on all three tasks. The highest accuracy for Transit Time (97.88%) and the stability in other tasks (around 82–83% for Ready to Serve Time and 81–82% for Service Time) confirm that DTP-ML does not need too many training runs to achieve optimal performance. The choice of 90–100 training runs is reasonable, balancing accuracy and computational efficiency, which is in line with the requirements of real logistics applications.

6. Conclusions. Our research introduces a machine learning-based framework for delivery time prediction, focusing on three critical time-related indicators in logistics operations: Transport Time, Ready-to-Serve Time, and Service Time. Through rigorous preprocessing – including feature engineering, label construction, and normalization – we prepared high-quality datasets using synthetic data from the VRPTW Homberger benchmark. To evaluate model performance across these tasks, we conducted a comprehensive set of experiments comparing several architectures, including Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and a customized machine learning training strategy (DTP-ML).

The data preprocessing pipeline played a crucial role in enhancing model effectiveness, involving feature extraction, label construction, and normalization techniques to ensure consistent input quality. Among the models evaluated, the proposed DTP-ML approach, based on Random Forests and trained across 90–100 iterations, consistently outperformed deep learning counterparts. It achieved superior performance with MAE values of 0.4203 (Transport Time), 0.3031 (Ready-to-Serve Time), and 8.5142 (Service Time), along with high prediction accuracy. In addition to its low error rates, the DTP-ML model demonstrated strong robustness and computational efficiency, requiring minimal hardware resources – making it a highly viable solution for real-world logistics optimization tasks.

However, we acknowledge several important limitations of the current study. First, our model uses Euclidean distance as a proxy for transit time, which does not capture real-world road network constraints such as travel paths, intersections, or dynamic traffic conditions. This simplification was necessary due to the structure of the benchmark dataset, which does not include graph-based road information. Consequently, our results may be less accurate when applied directly to real-world urban environments unless integrated with actual geospatial data and routing graphs. Future research should consider extending the current framework by incorporating graph-based routing data or using models designed for spatial networks.

Second, we recognize that the deep learning models originally selected (CNN, LSTM, GRU) are not inherently optimized for tabular data. Their inclusion was intended to explore their adaptability to non-sequential inputs. To provide a fairer comparison, we have introduced a fully connected neural network (FCNN) as a more suitable deep learning baseline and discussed state-of-the-art tabular architectures such as FT-Transformer and GLN, which we propose as important directions for future benchmarking and development.

In summary, this study contributes a scalable, interpretable, and computationally efficient model for delivery time prediction in VRPTW scenarios, with clear application potential in freight planning. Future directions for this work include:

– Integrating road network data to replace Euclidean distance approximation.

– Benchmarking against advanced tabular architectures like FT-Transformer and GLN.

– Integrating hybrid models that combine the interpretability and efficiency of tree-based models (like DTP-ML) with the learning capacity of deep learning architectures (e.g., CNN, LSTM).

– Applying the framework to larger-scale, real-world logistics datasets to validate generalizability across different domains and geographic contexts.

– Exploring online learning capabilities for real-time prediction updates in dynamic environments.

– Incorporating geospatial and temporal data fusion to further enhance model performance under complex delivery conditions.

These future extensions aim to strengthen the practical value and adaptability of machine learning in the evolving landscape of smart logistics and intelligent transportation systems.

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ПРИЛОЖЕНИЯ МАШИННОГО ОБУЧЕНИЯ ДЛЯ ПРОГНОЗИРОВАНИЯ СРОКОВ ДОСТАВКИ И ПЛАНИРОВАНИЯ ПЕРЕВОЗОК

Хунг Н.В., Ту Хуонг Т., Тан Н., Доан Т.К., Нам-Хоанг Н. **Приложения машинного обучения для прогнозирования сроков доставки и планирования перевозок.**

Аннотация. Стремительное развитие технологий оказывает огромное влияние на логистику и грузоперевозки. Эффективное управление графиками перевозок критически важно для предприятий, стремящихся минимизировать затраты, сократить задержки доставки и повысить удовлетворенность клиентов. Одна из ключевых задач в этой области – задача маршрутизации транспортных средств с временными окнами (VRPTW), которая требует не только поиска оптимальных маршрутов доставки, но и соблюдения определенных временных ограничений для каждого клиента или пункта доставки. Традиционные методы оптимизации часто сталкиваются со сложностью и динамичностью реальных логистических процессов, особенно при работе с большими объемами данных и непредсказуемыми факторами, такими как пробки на дорогах или погодные условия. Для устранения этих ограничений в данном исследовании представлена система на основе машинного обучения, которая повышает производительность существующих решений VRPTW. В отличие от традиционных подходов, которые полагаются исключительно на эвристику или статическое планирование, наша система использует современные модели машинного обучения для прогнозирования ключевых временных параметров, включая время доставки, время доступности и время обслуживания, на основе исторических и контекстных данных. Эти возможности прогнозирования позволяют алгоритмам маршрутизации принимать более обоснованные решения, что приводит к более точному и адаптируемому планированию. Опираясь на предыдущие исследования с использованием моделей случайного леса, мы предлагаем более надежную структуру, которая включает в себя передовые методы предварительной обработки и проектирование признаков для повышения точности модели. Обучая и оценивая систему с использованием реальных наборов данных, мы можем моделировать практические сценарии и подтверждать эффективность нашего подхода. Результаты экспериментов показывают, что предложенный метод стабильно превосходит распространенные модели машинного обучения с точки зрения средней абсолютной ошибки (MAE), тем самым подтверждая его потенциал для практического применения. Таким образом, данное исследование вносит свой вклад в масштабируемое и интеллектуальное решение давней логистической проблемы, открывая путь к более гибким и экономически эффективным транспортным системам.

Ключевые слова: задача маршрутизации транспортных средств с временными окнами (VRPTW), модели машинного обучения, оптимизация логистики, прогнозирование времени в пути, улучшение моделей случайного леса, методы обработки данных.

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