Optimal Route Planning System for Logistics Vehicles Based on Artificial Intelligence

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Abstract

E-commerce businesses have enjoyed drastic growth in sales numbers; subsequently, logistics businesses, who stands at the end of this commercial chain, have been receiving a rising number of service requests. The system utilizes Google Maps and its “multiple destination” function to search for possible routes. The routes undergo a multilayer perceptron model for traffic condition simulation. Finally, the system applies Dijkstra’s algorithm to identify the optimal route. The proposed system bears the following features: (1) a multilayer perceptron model is created using the history of traffic conditions; (2) the route planning considers traffic condition prediction based on the expected time of travel; (3) the optimal route is calculated using Dijkstra’s algorithm based on vehicle speed; (4) the system can include multiple destinations in its calculation, providing comprehensive travel plan for the logistics vehicle; (5) the system allows logistics business operators to keep track of their vehicles’ whereabouts and current traveling route. The system was implemented during experiments and proven to be feasible as well as effective in reducing idle driving and enhancing transportation efficiency. It is verified that the suggested system in this study has shown an outstanding performance from the experimental results; hence, the suggested system is capable of applying in realistic industry conditions.

Keywords: Path planning, Artificial intelligence, Multilayer perceptron, Internet of vehicles

1 Introduction

Nowadays, e-commerce has made its way into a clicks-and-mortar era; in this day and age of online shopping, going “mobile shopping” on mobile devices has become the mainstream mode. With shopping becoming so convenient, many e-commerce platforms have adopted a multi-channel approach to product promotion and marketing. The rise of e-commerce businesses has subsequently brought an influx of demand to logistics businesses; nevertheless, despite the demand, due to large capital investments as well as increase in labor and material costs, the logistics industry is actually facing low profits. One way to tackle this problem is to utilize algorithms such as big data analysis or artificial intelligence (AI) to help reduce transportation costs by optimizing travel routes, reducing fuel consumption, and dispatching vehicles effectively. While navigation systems currently available on the market are capable of route planning [1], the shortest path is not always the optimal path. Many navigation systems calculate travel time based on real-time road speed limit or road length (distance); however, other factors such as influx of cars during peak hours or real-time weather conditions might lead to traffic congestion and delayed travel time. Therefore, an optimal route can only be identified by taking into consideration a variety of factors. Idle driving resulting from an ineffective travel route will not only waste fuel consumption but also reduce transportation efficiency; thus, we need better ways to improve transportation routes for logistics vehicles.

Many studies have devoted to the calculation of optimal or shortest paths. [1] proposes using adaptation matrix for computing the optimal route. The study incorporates maps in its calculation. A shortest path on the map might not be the optimal route mainly because there might be obstacles between two points on the map; therefore, the study employs matrices to calculate the optimal route between a starting point and a destination point. [2] focuses on dynamic path planning. Since changes in traveling conditions can take place at any time during a trip, the study applies ant colony optimization to calculate the best route within a given area. The proposed algorithm can effectively resolve issues in dynamic path planning. On a similar note, [3] suggests using ant colony optimization to determine the optimal global path. The study adopts a two-step approach for optimal route

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planning; it also includes probability calculation in its model to increase the accuracy of route planning. Meanwhile, this study [4] investigates how to help emergency vehicles avoid traffic congestion when on the road. The study includes traffic congestion data in its dynamic calculation of travel routes to help emergency vehicles arrive at their destination in the shortest amount of time possible. The experiment results indicate that such algorithm is an effective one. Also focusing on emergency vehicles, this study [5] researches route planning for post-disaster emergency transportation. Since, in the past, the optimal path was determined by the shortest path, the study first creates a map including post-disaster conditions, and then applies ant colony optimization to calculate the optimal path. The study also incorporates integer linear planning (ILP) in its algorithm to improve computation efficiency. The above studies all reference the shortest path or traffic speed in their route planning; however, shortest paths or fastest paths involve a number of factors, such as rush hour or weather condition. Hence, such route planning requires weighted calculation of each road based on multiple factors before determining the optimal route. Optimal route planning can facilitate the transportation efficiency of logistics vehicles while reducing idle driving situations.

Our study proposes an optimal route identification system for logistics vehicles based on artificial intelligence. Currently available route planning systems focus only on time and distance; however, route planning requires additional information for consideration to yield an optimal route. Hence, we have included additional data such as traffic congestion history and weather condition into our calculation; we have also employed big data analysis to perform feature extraction on each road during different time sections. From there, we built an MLP model and, finally, applied Dijkstra's algorithm based on vehicle speed to run our optimal route calculation. The proposed system is capable of calculating an optimal route for a multi-stop travel. It can provide a comprehensive travel plan and helps logistics business operators keep track of their dispatch vehicles. The system bears the following features: (1) It utilizes variegated data to predict traffic congestion. (2) It utilizes big data analysis to analyze a road's traffic conditions at different times while also flagging any traffic congestion. (3) It builds an MLP model through data analysis to predict traffic congestions. (4) It enables multiple destinations in its route planning, helping logistics vehicles devise a comprehensive travel plan. (5) The system applies a Dijkstra's algorithm based on vehicle speed to calculate the optimal route. (6) Logistics business operators can utilize their logistics vehicle's Global Positioning System (GPS) and our systems planned route to determine whether the vehicle has strayed from the path. The main features of the system in this research are as follow: 1. decreasing the circumstances of idling speed caused by traffic jams; apart from affecting delivery effectiveness, idle speed also increases fuel consumption; 2. improving delivery effectiveness is beneficial to delivery times. The study utilizes transportation records and climate conditions to build an MLP model; furthermore, delivery vehicles could use the MLP model to plan optimized routes. The experimental result of this research has proved that this method is feasible in practical conditions.

2 Related Works

[6] employs Dijkstra's algorithm to identify the optimal route. The study also uses the matrix position of the vector matrix as the node to determine which nodes the robot must pass through and then calculate the optimal route. The study also uses the matrix position of the vector matrix as the node to determine which nodes the robot must pass through and then calculate the optimal route. [7] uses drones and a variety of traffic information to determine the optimal route. It utilizes the notion of set statistics to perform road segmentation and yield the optimal result. [8] adopts traveling time estimation (TTE) for optimal route planning by including data such as traffic light duration in its TTE calculation. Optimal route planning requires low-complexity computation. Aside from traffic light information, the study also factors in traffic data regarding vehicles on the road to achieve real-time route planning. [9] provides multiple options in its route planning. Many navigation systems focus on time or distance in their route planning; however, this study employs heuristic algorithm for multi-destination route planning. The heuristic algorithm utilizes data on traffic history and demographic structure to perform optimal route planning. Another study that also provides rich options is [10], which proposes a multi-stop route planning approach. While many studies base their optimal route planning on the origin and the destination, this study's system follows changes in different destinations and makes subsequent adjustments by recalculating the optimal route. The study makes use of artificial neural networks (ANN) to compute all possible paths between one stop and other stops before determining the optimal path. [11] posits that, aside from time and distance, route planning should take into account factors such as road comfort and road traffic anomaly incidence. With this in mind, the study employs the Internet of Vehicles (IoV) to collect relevant data, analyze each road's traffic anomaly incidence rate, and survey road width, all of which are taken into consideration in its route planning so as to offer drivers and passengers a comfortable driving environment during their trip.

Also referencing IoV, [12] utilizes IoV to collect real-time traffic information to help vehicles adjust their routes at any time needed. Meanwhile, [13] discusses how applying the traditional geographic information system (GIS) in a smart city will not satisfy the system needs. Hence, aside from road traffic information, the GIS should include more information about the urban area, such as demographic structure and transportation, so as to enable the systems within the smart city to swiftly access data, perform calculation, and provide a more accurate and better tailored service. On the note of smart cities, [14] suggests that smart cities apply vehicle sensor data to compute situations such as road safety and traffic congestion. Meanwhile, [15] discusses the use of game theory with IoV to distribute vehicle message transmission conditions and improve network quality. [16] employs caches for storage of navigation routes; it also uses prediction routes to prevent GPS failure and subsequent malfunctioning of the navigation system.

[17] uses rapidly-exploring random trees to discern the optimal route while [18] applies a hybrid neural network model to calculate road-related data and identify a road's risk index. Meanwhile, [19] offers route optimization for cargo fleets on transportation missions. The study adopts dynamic detection for traffic congestion and constantly recalculates and readjusts each vehicle's travel route to maximize the cargo fleet's transportation efficacy.

Some of the researches that have chosen to apply deep learning in their study of roads or vehicles include the following. [20] suggests that the main task of IoV is ensuring vehicle safety. Currently, vehicles can only obtain real-time traffic conditions via the Internet; the study applies deep learning to compute vehicle sensor data and traffic information to determine whether the driver is performing dangerous driving. Another study that adopts deep learning is [21, 24-27], which utilizes deep learning to improve IoV's network quality. The study first determines whether a packet is front-end or backend before submitting it for processing, an approach that speeds up the network's transmission speed. An integration of fog-cloud computing and IoV also reduces delays in network transmission. [22] adopts deep learning to monitor a vehicle's movements and behavior to determine whether the driver is committing dangerous driving. [23, 28-30] takes all kinds of vehicle and traffic information in a smart city and applies deep learning towards them to predict traffic congestions and traffic light timing. [23] conducts traffic congestion prediction via deep learning and calculates the optima route using Dijkstra's algorithm. The main feature of this study is that it utilizes data on traffic history and weather to build a multilayer perceptron model to determine each road's traffic condition. The scheme can effectively and accurately calculate the transportation time needed for a logistics vehicle.

3 The Proposed Scheme

In this section, we will introduce the system model (3.1), big data analysis (3.2), AI-based route planning (3.3), and our speed-based Dijkstra's algorithm (3.4).

3.1 System Model

The software development for in this study are developed via module, with the system illustration as shown in Figure 1. We first collected data on roads, traffic, and weather and created an MLP model. Prior to assigning a vehicle to task, the dispatch center will analyze each vehicle's cargo volume and traveling route for the day; hence, the route planning must be conducted speedily and accurately. The dispatch center will then arrange the deliveries in order of time and proceed to yield a multiple-destination comprehensive route planning for the logistics vehicle. Vehicles on dispatch (V_1, V_2, and V_3) will report their GPS information back to the dispatch center, who will then analyze the driver's behavior and whether the vehicle has strayed from its planned route. When the cargo reaches the delivery address and the driver opens the trunk to retrieve the goods, messages and photos are taken and sent back to the dispatch center, who is then aware of whether the cargo has reached the recipient. Following the above, the dispatch center will collect all data for analysis and report whether any anomaly has been detected. In case of anomaly, a notification is issued, and the administrator can access the anomaly conditions using their mobile device while being outdoors without access to computers. The administrator can also use their mobile device to keep track of each logistics vehicle's work progress. In the future, we can further extend this study's research and include additional features. For instance, if there is any error in the delivery address, the system can issue a warning. The dispatch center can calculate a driver's traveling time and, when it exceeds the regulatory hours, the system will issue a warning. After a vehicle leaves for a task, the dispatch center can calculate the driver's accumulated work hours and cargo delivery volume and translate them into charts and reports.

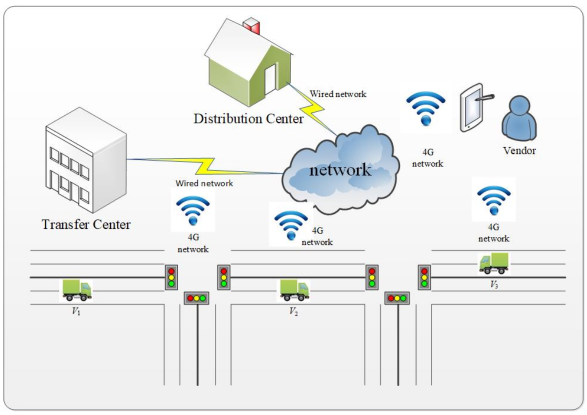

Figure 1. System illustration

3.2 Big Data Analysis

We collected information on each road's traffic congestion and weather condition at different times, and then utilized data on relevant government websites to build a database. First of all, prior to storing the data, we run procedures such as data cleansing and format unification. Our system will access data from the database, apply k-means clustering for data clustering and feature training, and apply multidimensional clustering for conducting predictions. In the system, suppose the data of roads in each area is $A_i = \{R_{a,t,1}, R_{a,t,2}, ..., R_{a,t,n}\}$, in which $R_{a,t,i}$ stands for a road's data at a given period of time, with a representing the area and t representing time. The system calculates the k-means structure, given predefined k number of clusters and $WK_{t,i}$ as the cluster's center, as shown in Figure 2.

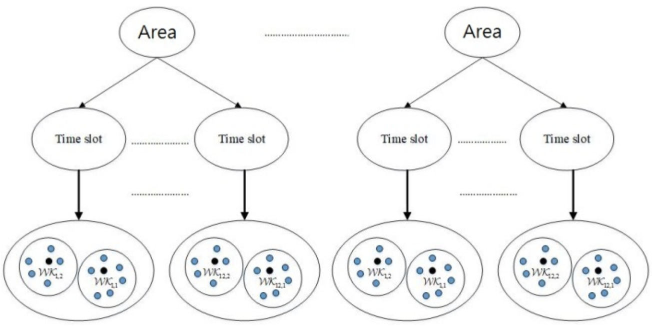

Figure 2. Cluster illustration

Step 1: First, the data is classified based on area (A_i).
Step 2: Data in the area is then classified as road or highway.
Step 3: Next, each road or highway is classified as a morning/afternoon time period of a weekday/holiday.
Step 4: $WK_{t,i}$, the cluster head, is then classified as a morning/afternoon time period of a weekday/holiday.
Step 5: Given $WK_{t,i}$, the system first determines what the weather condition is and then classifies $WK_{t,i}$ into two sets – sunny day and rainy day. Following that, the system calculates the average of the set.
Step 6: Next, the system marks the set features of each $WK_{t,i}$, such as the road's average speed, time period, and weather condition.

3.3 Artificial Intelligence-Based Route Planning

This section discusses traffic congestion prediction. Prior to making such predictions, the system will have already arranged the delivery order of different cargo based on the needs and demands of the recipient into delivery stops A, …, G. In this section, we will use Google Maps to calculate all possible routes between stop A and stop B, and then utilize the algorithm proposed in the following to predict the traffic congestion situation for all possible routes between stop A and stop B. Artificial neural networks (ANN) were mainly developed for machine learning. Artificial neural networks are capable of predicting and decision-making, and they can offer applications such as license plate identification, speech recognition, and face recognition. An MLP model is a forward propagation artificial neural network that contains at least three layers of structure – the input layer, the hidden layer, and the output layer. This study uses an MLP model to predict traffic congestions. Analysis results from Section 3.2 are used to build the MLP model. This study applies big data analysis to mark features of roads such as speed limit, time of day, average values, and weather conditions. The road features are then submitted for creation of the MLP model, as shown in Figure 3. Of all the included data, this study used 80% of it to build the model and 20% of it for model validation; the algorithm employed is as follows:

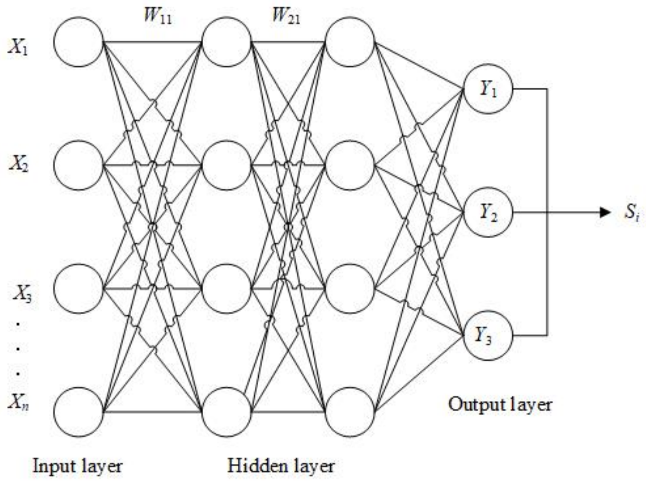

Figure 3. The MLP model

(1) Suppose the input layer data is $X_1, \ldots, X_n$, with each piece of data containing four input values.

(2) The value input into the hidden layer is z_i and suppose that it learns a linear pattern between input and output. The intermediate hidden layer is $z_i = \sum_{i=1}^{n} w_i X_i + b$, in which w_i stands for weighting, b stands for bias, and every node in the hidden layer is expressed in vector.

(3) The system computes the neurons in layer l-1 by outputting z_i towards neurons in the l layer via the following equation: $a_j^l = \sigma\left(\sum_{k-1}^{m} w_{jk}^l z_k^{l-1} + b_j^l\right)$.

(4) In order to reduce computational complexity, we utilize vectors to simplify the computation. The equation is $a^l = \sigma\left(z^l\right) = \sigma\left(w^l a^{l-1} + b^l\right)$ and the result obtained is a^l.

(5) In regard to activation function, the system applies hyperbolic tangents and rectified linear units. The value of each input layer after input is a^l. The

equation is $a^l = \sigma\left(w^l a^{l-1} + b^l\right)$.

(6) Following the above, the gradient descent searches for the optimal parameter. The output layer is Y_i, which stands for the prediction of traffic congestion situation. Next, the system calculates a road's congestion rate, $S_i = SP * ST_i$, in which ST_i represents traffic speed during congestion – 100% signifies regular speed, 70% signifies light congestion, 50% signifies heavy congestion, and SP represents the road speed limit.

When the MLP model is complete and established, each day, the dispatch center will analyze each logistics vehicle's tasks and locations. The system utilizes Google Maps to calculate the multiple possible routes between any two points. Our system enters each node's origin-to-destination route into the MLP model to run prediction. Input data include information such as road speed limit, time of day, average values, and weather condition. The MLP will then offer a prediction of traffic speed and, subsequently, be able to determine the optimal route for the transportation journey.

3.4 A Dijkstra's Algorithm Based on Speed

This section centers around identifying the optimal route between the previous delivery stop and the next delivery stop. When the MLP model has completed running its predictions, it will proceed to calculate the optimal travel route. First, the calculated prediction result is $P_i = \left\{PR_{a,t,1}, PR_{a,t,2}, \ldots, PR_{a,t,n}\right\}$. The study hypothesizes a directed graph, G. V represents the set including all nodes, $\left\{PR_{a,t,1}, PR_{a,t,2}, \ldots, PR_{a,t,n}\right\} \in V$. The multipath between the apex and the destination is (u,v) and the edges, E, between nodes predict speed. The system runs a cumulation of the edges (E) of every route and identifies the maximum value as the optimal route. The equation is as follows:

$$(u,v)_i = \sum_{j=1} E_{i,j} \tag{1}$$

When the system has calculated the cumulative value of each road's edges, it will compare the values and declare the maximum value to be the optimal route. This is because the road with the highest speed entails the lack of idle driving on that road as well as swift arrival to the destination. This study adopts a multiple-route planning approach. Suppose a logistics vehicle must make deliveries to n destinations. Our system will calculate one-by-one all possible routes between the first destination and the nth destination and then determine the overall optimal route for that vehicle, which should maximize business profits and transportation efficacy.

4 Experiment Results

This section elaborates on the proposed fleet management system's experiment results as well as optimal route experiment results.

4.1 Fleet Management System

The proposed fleet management system is capable of tracking a vehicle's traveling route. The management system incorporates Google Map; logistics vehicles report back their vehicle location and speed via GPS packets. Figure 4 shows an illustration of a vehicle's trajectory; we can learn from such trajectory whether a vehicle has strayed from its originally planned path. Each point on the map exhibits the time that the vehicle passed through it. This allows us to access real-time progress of any given logistics vehicle as well as keep track of its average speed, distance traveled, and time spent in idle driving. As shown in Figure 5, the system can export charts and reports illustrating information such as a vehicle's current travel distance, time of departure, and cumulative idle speed time, which helps us keep track of a logistic vehicle's transportation efficacy as well as its whereabouts.

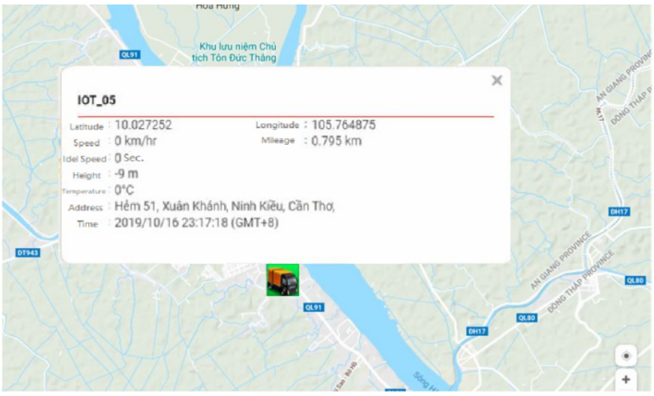

Figure 4. The trajectory of a vehicle

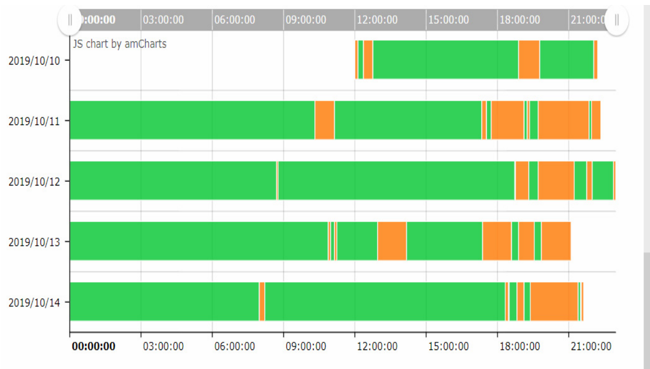

Figure 5. The charts and reports function

4.2 Results of Planning Routes

We collected a total of 1500 pieces of road-related information and 700 pieces of weather information; among the data, 80% of it was used to create the MLP model while the other 20% was used for model validation. As illustrated in Figure 6, the study validated 300 pieces of information and the MLP model achieved an accuracy of 95%, which proves that our proposed MLP model is highly accurate and can be effective in predicting a logistic vehicle's driving conditions and speed, which will in turn enhance transportation efficiency as well as reduce chances of idle driving. The system was trained more than 170 times with stable predicted results, which proves that the system of this study could predict the conditions of traffic congestion accurately and improve the delivery effectiveness of logistics vehicles for planning the routes.

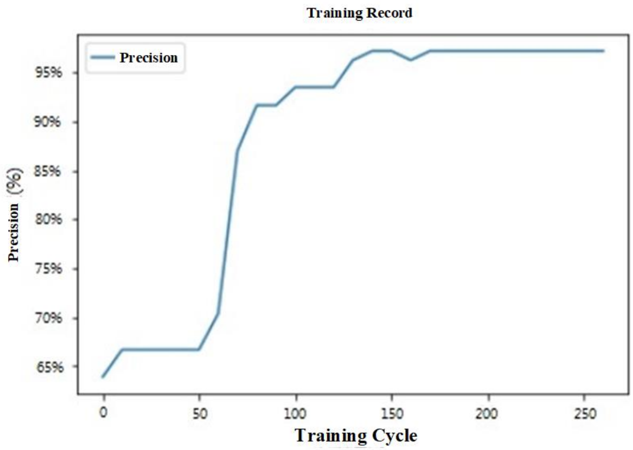

Figure 6. The MLP model's accuracy curve graph

5 Conclusion

Nowadays, logistics businesses rely mostly on navigation systems or maps to plan their transportation routes. However, navigation systems and maps are not yet capable of taking into account real-time traffic flow and weather conditions; hence, their suggested travel route is not always the optimal route. In order to help logistics businesses reduce labor costs and increase profits, this study proposes an AI-based optimal route identification system for logistics vehicles. The system provided by this research could enhance delivery effectiveness and decrease the condition of idle speed; additionally, the method in the study adds the information of the transportation records and the climate conditions to develop an MLP model for growing the forecast accuracy precisely. Experiment results show that that our system can achieve a prediction accuracy rate of 88%, indicating that the proposed scheme is feasible. In the future, we will incorporate sensors to create a cold chain logistics vehicle monitoring system that will allow dispatch centers to monitor the delivery destination and arrival time of any given vehicle. Our system is designed to be financially affordable to better service middle and small businesses elevate their competitiveness in the industry. The prediction result of the system has reached over 95% accuracy, which demonstrates the high feasibility of the system.

Acknowledgments

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Biographies

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