Prediction Method of Truck Travel Time in Open Pit Mines Based on LSTM Model

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Abstract: Aiming at the prediction of truck travel time in open pit mines, we established a prediction model based on long short-term memory(LSTM). This model fully accounts for 11 factors, including the nature of trucks, weather, road conditions, and driver's behaviors, as well as the influence of neighbor road segments in the route on the current predicted road segment. The experiment shows that the error of the LSTM prediction model is significantly reduced compared with SVR and BP models. In addition, the maximum absolute mean error under different conditions is less than 12 seconds.

Key Words: Travel Time Prediction, Open Pit Truck, LSTM

1 Introduction

Truck transportation is a crucial component of the open-pit mine industry, and its mining and transportation costs make up more than 60% of the mine's overall output costs. Therefore, open-pit truck scheduling system is constantly being developed in order to increase mining efficiency and lower running costs. It is inevitable that it will play a key role in the advancement and upgrading of the scheduling algorithm through the analysis and processing of the vast amounts of data produced in the system. The use of accurate travel time prediction is conducive to reducing truck queuing time, thus greatly improving production efficiency and reducing costs.

In terms of travel time prediction of open-pit mine, Sun et al. [1] used the average of truck travel time as the predicted value of travel time to establish a mathematical model for the running time statistics of mine road segments transported by multiple types of trucks. Zhang et al. [2] proposed the non-stationary time series ARIMA model to predict this kind of time parameters, and proved that the prediction formula of time series model can predict a kind of mine time parameters. Bai et al. [3] proposed a multi-factor prediction neural network travel time prediction function model, proved that travel time prediction function is a complex nonlinear functional relationship, and pointed out the shortcomings of single-factor prediction method. However, the model has local minimum points, which lead to slow convergence and multiple iterations. In order to make travel time prediction have real-time, reliability and higher accuracy, Li et al. [4] established a real-time prediction model of travel time of truck road segment based on fuzzy neural network reasoning system (ANFIS).

In addition, prediction models can be built by computer simulation software. Chanda et al. [5] conducted a comparative study on TALPAC software simulation, ANN and multiple regression (MR) three time prediction models to determine the best method of travel time prediction. The results show that the prediction ability of neural network and regression model based on actual mine data is better than that of TALPAC computer simulation software.

In view of the shortcomings of the existing multi-factor prediction BP neural network travel time model, Xue [6] proposed a selective integrated learning algorithm based on least square support vector regression (LS-SVR), and conducted experiments on the actual collected data of open-pit coal mine, and obtained a high prediction accuracy, which demonstrated the effectiveness and real-time performance of the algorithm. Meng [7] compared the results of BP neural network and support vector machine in the prediction of travel time, selected the prediction model based on SVM, and obtained the prediction of vehicle-path travel time in the next stage of the scheduling time, which was used as a parameter to improve the scheduling model, and further improved the accuracy and reliability of the dynamic scheduling model.

In recent years ,machine learning has become the main method for prediction of truck travel time in open pit mines. Sun [8] combined the machine learning method with big data to predict the real-time link travel time of open-pit truck scheduling, and took into account the influence of meteorological characteristics on the model. Gu et al. [9] proposed a method of SVM parameter optimization based on genetic algorithm, and built a truck travel time prediction model based on HGSVMA model, whose accuracy is higher than that of GS-SVM and other models. Choudhury et al.[10] used kNN, SVM and RF to predict the travel time of mine dump trucks under different atmospheric conditions. Tian et al. [11] constructed a velocity field according to the truck velocity information to obtain the average speed of trucks in each road segment, which was used as the input feature of the random forest road segment unit travel time prediction model, and then accumulated the predicted value

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of each unit prediction model to obtain the predicted value of truck travel time on the composite road segment.

The current methods for predicting truck travel time in open-pit mines usually divide the whole route of trucks from the starting point to the end point into independent road segments (or called links), but ignore the influence of neighbor road segments in the route on the current predicted road segment. In order to improve the accuracy of the optimized scheduling system for open-pit trucks, and considering the influence of the sequence of continuous road segments, a prediction model for truck travel time in open-pit mines based on LSTM is proposed, which significantly improved the accuracy compared with the traditional prediction methods.

2 Prediction Model of Truck Travel Time in Open Pit Mines

2.1 Feature Selection

Trucks are often affected by a variety of factors when driving. External circumstances such as gradient, road conditions and weather conditions are the main reasons for fluctuations in travel times when driving in different road conditions. Factors such as the type of vehicle and the driving habits of the driver can also cause travel times to vary.

Travel time is mainly affected by four aspects:

One is the nature of the trucks themselves. Different trucks have different performance and transport capacity. Load capacity is an important factor affecting truck travel time. If the output of the truck is constant, the heavier the load, the lower the speed.

Second, road characteristics, including road type, road gradient and turning angle. According to the road rolling resistance coefficient (also known as the friction coefficient, refers to the ratio of the thrust required by the wheel and its load during the driving process), the pavement types are divided into several types as shown in Table 1.

Table 1: Rolling Resistance Coefficient

Pavement Type	f
Good asphalt or concrete pavement	0.0.0∼0.018
General asphalt or concrete pavement	0.018∼0.020
Gravel pavement	0.020∼0.025
Good pebble pavement	0.025∼0.030
Potholed pebble pavement	0.035∼0.050
Compacted dirt road (dry)	0.025∼0.035
Compacting dirt road (after rain)	0.050∼0.150

Different tonnage of Open-pit trucks correspond to different power and different road gradients produce different driving resistance [12]. Assuming that all Open-pit trucks are electrically driven, the literature [13] gives the relationship between road gradient, motor power and transmission ratio, fully loaded gross mass and driving speed:

$$u_i = \frac{3600\eta P}{mg(f+i)} \tag{1}$$

where u_i is the speed of the open-pit truck on a road with gradient i, km/h; η is the total efficiency of the transmission, 0.8 $\sim$ 0.9, up to 0.95; P is the maximum output power of the motor, kW; m is the total mass of the open-pit truck, kg; g is the acceleration of gravity, 9.81 $\mathrm{m/s^2}$; f is the rolling resistance coefficient; i is the gradient, %.

Thirdly, the driver's behavior. The subjective factor that has the greatest impact on the speed of a truck during its travel is the driver himself. The variability of the driver's individual driving habits or functional needs can lead to frequent shifting behaviour, and the changes in speed caused by this behavior can have an impact on the truck's travel time on the roadway.

Lastly, weather conditions can adversely affect the driver's driving vision, resulting in a reduction in driving speed, while changes in the degree of slippery road surface in adverse weather conditions can also reduce driving speed. The effects of three weather characteristics, sunny, rainy and foggy, are included to take into account the contingent nature of the occurrence of extreme weather. In addition, the difference in road visibility between daytime and nighttime also affects the driving speed to a great extent.

Through the above analysis, 11 variables are finally selected as model input features in these four aspects, and the Table 2 describes the input variable types and value ranges.

Table 2: Description of the Input Variables

Variables	Type	Range of Values
Truck type	Categorical	28t,50t,65t and 220t
Truck state	Categorical	load and unload
Speed	Numeric	0∼40km/h
Link length	Numeric	not fixed
Link width	Numeric	not fixed
Gradient	Numeric	not fixed
Pavement quality	Numeric	0∼0.050
Number of turns	Numeric	not fixed
Driver's behavior	Numeric	0.0∼0.5
Weather	Categorical	sunny, foggy and rainy
Time period	Categorical	daytime, nighttime

2.2 Structure of the Road Network

To complete the basic mining, transportation as well as unloading and discharging work in an open pit mine, it is necessary to link the load points, the dump points and the access trenches between the flat pan and the discharging site. The transport network of an open pit mine is to establish certain connections through functionally different transport routes such as production trunk lines, branch lines and liaison lines.

Referring to the road network structure in [14], this includes five load points and three dump points as well as 13 numbers of intersection nodes, which are divided into 24 road segments based on road attributes. The depth-first traversal algorithm searches for all paths between any load point and any dump point, and avoids the occurrence of closed loops in the paths, allowing a total of 111 optional paths to be found.

2.3 LSTM Neural Network

The LSTM model [15] is derived from the deformation of Recurrent neural network(RNN). RNN can be seen as an improved result of multilayer perceptrons, which have significant advantages in dealing with time-series-like problems and are widely used in generating sequences, text translation

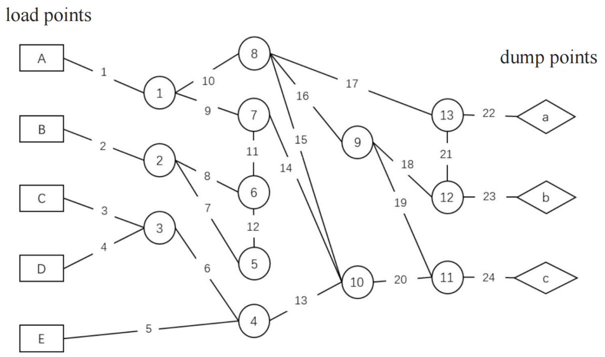

Fig. 1: Road network of open-pit transportation system

and prediction. RNNs consist of three layers: input, hidden and output, where the way to establish the connection between the hidden layers is through the time series. When expanded in time, it is seen that the input at each moment includes both the output of the hidden layer of the network at the previous moment and the input at the current moment. Therefore, the historical information is included in the output of the hidden layer of the network at the current moment, showing the ability to remember historical information.

RNNs compute errors by Back-Propagation Through Time (BPTT), but this method does not solve the problem of frequent gradient disappearance or occasional gradient explosion due to the long time series of data association problems. Gated RNNs exist to solve such problems, and one of the most widely known is the LSTM.

The LSTM does not change much from the RNN in terms of its overall structure, but mainly improves the hidden layer. The units in the hidden layer are called memory modules, and their composition consists of a storage unit as well as three computational components. A brief description of each component is given below, mainly in terms of structure and function.

- Forget gate. The forget gate, which in some ways discards useless information, is mainly concerned with the output h_{t-1} at the current moment and the input x_i at the current moment. The value between 0 and 1 indicates the degree of forgetting.
- Input gate. The input information of the network is controlled by an input gate. New vectors are generated through the tanh layer. $i(t)$ and $g(i)$ together make up the input gate, so updating the state of the input gate requires updating both parts to determine what information is stored in the cell.
- Output gate. The output gate controls the output information of the network. First determine what the output data or information is, and second multiply the input via the sigmoid function with the data or information that needs to be output via the tan layer, so that the value of the cell state can be in the range of -1 to 1, that is, the state information of the output gate.

The three gates in the LSTM model have the same logical unit structure and consist of a Sigmoid function σ and a dot product operation $\times$. The sigmoid function is often used as an activation function in neural networks. Its role is to be able to introduce a non-linear element to the LSTM network and because of its limited output range can ensure a clustered type of information in the transfer process. The vector is restricted to 0 to 1 after the sigmoid function layer, with 0 representing "no pass at all" and 1 representing "pass at all".

As shown in Figure 2, the four structural layers of the LSTM act in connection with each other. The boxes show the activation functions in the memory module, the circles show the addition and multiplication of vectors and the arrows point in the direction of the transfer in the structure. The black line represents the output of a vector from one node to another, the interaction of several lines represents the merging of vectors, and the division of one into multiple lines represents the copying of vectors. The lines crossing the model represent the transfer of cell states from the previous moment to the current moment, enabling a linear interaction of information. The update of cell states is achieved by gates, sigmoid layers, and dot product operations to filter the information.

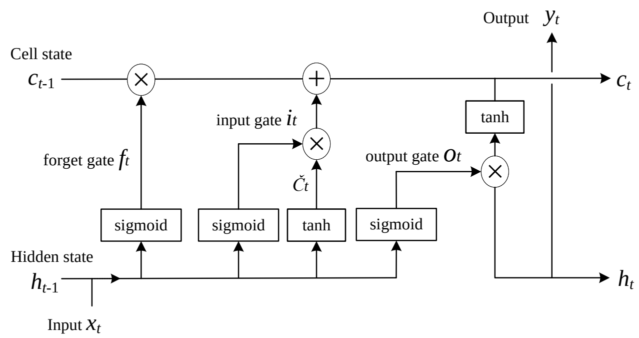

Fig. 2: LSTM neurons

2.4 Prediction Model

LSTM neural network is used to establish the truck travel time prediction model of the open pit mine. The general flow of the model algorithm is as follows.

Step 1 Data Partitioning and Preprocessing. The data is divided into two parts: the training set and the verification set, the input and output variables of the LSTM model are determined, and all data are standardized.

Step 2 LSTM Model Prediction. Test out the basic range of each parameter in LSTM based on existing experience and refine the model structure. Load the data of the training set into the LSTM model, and then complete the training of the model through the loss function and optimization function. Finally, the data from the test set is loaded into the trained LSTM model to obtain the predicted travel time of each road segment.

The LSTM model has a more complex internal structure than a typical artificial neural network. Figure 3 expands it in chronological order. Vertically, the three nodes represent the input, hidden, and output layers of the LSTM network. Horizontally, each node represents a different section of the computational process.

Suppose there are n links and each link data $x^{(n)}$ contains 11 features $[x_1, x_2, ..., x_{11}]$ that affect the truck travel time. $k+1$ is the LSTM time step, which takes the value of 3. Here the data $x^{(n-2)}$ at the link $n-2$ is input into the LSTM model, output via the hidden layer, and input to the $n-1$

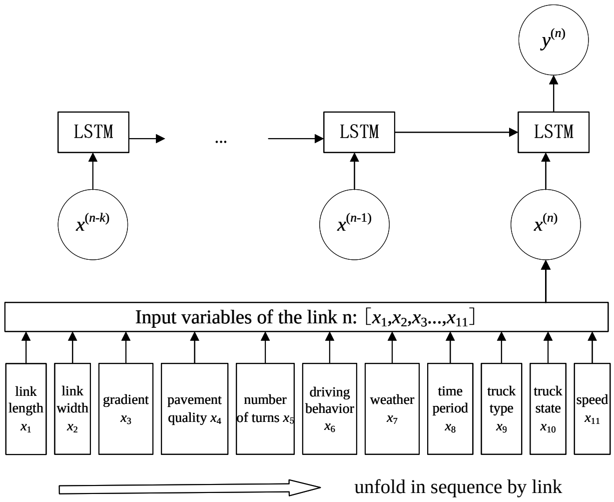

Fig. 3: Schematic diagram of LSTM prediction model

LSTM model together with the input data $x^{(n-1)}$ for the link $n-1$, which is then output via the hidden layer. In this way it is passed to the hidden layer of the link n and finally transmitted to the output layer. In this case, the hidden layer is calculated as follows.

The LSTM contains three thresholds and cell states each with its corresponding equation. By following equations 2 to 7 the current output value of each state can be found.

The input to the forget gate is obtained by combining the input variable x_t, i.e. $x^{(n)}$, at moment t with the output h_{t-1} of the hidden layer at moment $t-1$ to obtain the output value of the forget gate at that moment:

$$f(t) = \sigma\left(W_f \cdot [h(t-1), x(t)] + b_f\right) \tag{2}$$

where $f(t)$ represents the output value of the forget gate state at moment t; σ is the sigmoid function of the forget gate; W_f and b_f are the weight matrix and bias matrix respectively; $h(t-1)$ is the output at moment $t-1$, i.e. the running time of the section $n-1$ at moment $t-1$; $x(t)$ i.e. $x^{(n)}$ is input variables of the link n at moment t;

And for the input gate, the states $i(t)$ and $\widetilde{C}(t)$ to be updated and retained:

$$i(t) = \sigma\left(W_i \cdot [h(t-1), x(t)] + b_i\right) \tag{3}$$

$$\widetilde{C}(t) = \tanh\left(W_c \cdot [h(t-1), x(t)] + b_c\right) \tag{4}$$

where $i(t)$ represents the information that needs to be updated at moment t; σ is the activation function sigmoid function of the input gate; $\widetilde{C}(t)$ is the information to be retained obtained at moment t through the tanh layer.

The cell is updated from the state $C(t-1)$ at moment $t-1$ to the state $C(t)$ at moment t by the equation:

$$C(t) = f(t-1) * C(t-1) + i(t) * \widetilde{C}(t) \tag{5}$$

where $f(t-1)*C(t-1)$ is the degree of forgetting; $i(t)*\widetilde{C}(t)$ is the added information, i.e. the product of the information to be updated and retained that passes through the input gate.

The output gate determines the output information of the network and the state equation is

$$o(t) = \sigma\left(W_o \cdot [h(t-1), x(t) + b_o]\right) \tag{6}$$

$$h(t) = o(t) * \tanh(C(t)) \tag{7}$$

where $o(t)$ is the output cell state after a sigmoid function; $h(t)$ is the output gate state obtained by multiplying the input $C(t)$ by $o(t)$ after the tanh function, i.e. The travel time on the link n obtained after the action of the hidden layer at moment t.

3 Experimental Studies

The experiments are conducted using the Pytorch deep learning framework. Firstly, the dataset is partitioned and all input data is normalized in order to eliminate numerical problems caused by too large values of some variables leading to too small weights. Next, the parameters of the network model is set, which requires a given time step and batch, setting the input and output dimensions, determining the number of layers and nodes in the hidden layer, selecting a loss function and an optimization function to optimize the model, and finally validating the model performance through evaluation metrics.

3.1 Dataset

There are currently no physical models for the full range of surface mine truck travel times to describe the process. Based on the actual situation and the existing experience it is possible to simulate the equation of the relationship between each factor and the target value. The distances and elevation differences of the road segments between the nodes in the mine road network map are obtained and, after reasonable normalization, used as the lengths of the corresponding road segments, and the segment quality and number of turns for each segment in the map are noted. As the five road attributes of each segment are fixed, the remaining six variables are changed separately to calculate the travel time of 111 paths on each segment in turn, each segment data is a sample, and finally 59940 sample data are obtained.

3.2 Parameters Setting

The travel time of a truck traveling a certain roadway distance is not necessarily fixed due to the fact that it is affected by a variety of factors, so it is necessary to incorporate as many external environments as possible, such as road environment and weather conditions, as well as human factors such as driver's behavior, to improve the accuracy of the prediction model.

Based on the analysis of the influencing factors of truck travel time, the features of link length x_1, link width x_2, average gradient x_3, pavement quality x_4, number of turns x_5, driver's behavior x_6, weather x_7, time period x_8, truck type x_9, truck state x_{10}, and speed x_{11} are selected as the influencing factors of truck travel time prediction. Therefore, 11 neurons are used in the input layer and 1 neuron is used in the output layer.

In the LSTM prediction model, the tanh function is generally chosen as the default activation function and the mean square error function MSE is chosen as the loss function. Considering the continuity of the sample space and the characteristics of other common optimization methods, Adam, which has better performance, is selected as the optimization function.

Model performance index evaluation is a basic way to verify the accuracy of model training. In order to show the actual value of error more intuitively, the absolute mean error (MAE) and mean absolute percentage error (MAPE) are chosen to evaluate the model prediction effect.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \tag{8}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{9}$$

where n represents the number of samples involved in the evaluation, and $\hat{y}_i$ and y_i denote the predicted and true values, respectively. the absolute mean error (MAE) represents the average deviation between the predicted and true values. From equation 8, it can be seen that the smaller the MAE is, the smaller the gap between the predicted and true values.The mean absolute percentage error (MAPE) represents the relative mean deviation, and the closer its value is to zero, the more accurate the prediction will be. Of the two performance evaluation indicators, MAPE is a relative ratio, which is more objective than the absolute value.

3.3 Experimental Results

The first 70 path data are selected as the training set and the last 30 path data are used as the validation set. To evaluate the prediction effect of the LSTM model, the prediction results of LSTM are compared with those of two traditional open pit mine truck travel time prediction methods, SVR and BP, and the comparison results are shown in Table 3.

Table 3: Comparison of evaluation indexes of the three prediction models

Model	Evaluation	value
SVR	MAE(s)	3.58
	MAPE(%)	16.2
BP	MAE(s)	2.86
	MAPE(%)	11.6
LSTM	MAE(s)	0.848
	MAPE(%)	2.61

By comparing the evaluation indexes of each model in Table 3, it can be seen that the accuracy of the LSTM model predictions are significantly improved compared with the traditional SVR and BP methods, indicating that the use of the LSTM model can significantly improve the accuracy of predicting the travel time of the open pit trucks.

In order to verify the degree of influence of multiple factors on the driving conditions and on the accuracy of the predicted values of the LSTM model for each link, the trend of the travel time and the error between the predicted and true values are observed when a single factor variable is changed without changing other factors. The shortest path from loading point E to dump point a is selected as the test object, which passes through links 5-13-20-19-18-21-22.Table 4 shows the link properties of path E-a.

Figure 4(a) shows the fitting effect of the LSTM model on the test data when the weather conditions are sunny, foggy

Table 4: link properties of path E-a

link	length	width	gradient	quality	turns
5	73.11	0.95	0.18	0.025	3
13	1020.4	0.95	0.06	0.035	1
20	627.149	1	0.17	0.02	0
19	2373.11	1	0.4	0.02	3
18	640.865	1	0.02	0.02	0
21	1268.43	1	0.33	0.035	1
22	29.25	0.95	0.1	0.025	1

and rainy respectively. As shown in the figure, the predicted distribution of travel time on all links is the longest in rainy days, followed by foggy days and the shortest in sunny days, which is in line with the predicted change trend.

Figure 4(b) shows the absolute error of the predicted travel time of each link of the path under three different weather conditions. The maximum error is less than 12 seconds on a rainy day, indicating that the predicted results are accurate.

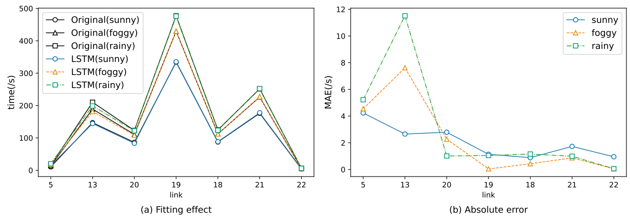

Fig. 4: Forecast results under three different weather conditions

Driver's behavior is also an important factor in the change in travel time. Larger values of driver's behavior in Figure 5 indicate that the more frequently the driver occurs shifting behavior, the shift duty cycle increases, and the travel time for each link decreases further. The true value in Figure 5(a) reflects this process, while the predicted value can also see this change process. Combined with the average error in Figure 5(b), it can be seen that the absolute average error does not exceed a maximum of 5 seconds, which satisfies the prediction accuracy requirement.

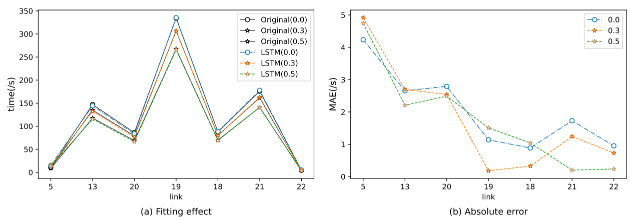

Fig. 5: Forecast results under three different driver's behaviors

In practice, the travel time of the truck on the road segment increases correspondingly with the increase of the load. The relationship between the travel time and truck state for each link on the predicted path is shown in Figure 6(a), in which it can be seen that the travel time of the truck under different load conditions varies significantly, and it often takes more time when it is heavily loaded compared to the unloaded state. The maximum absolute average error is shown in Figure 6(b) to be no more than 5 seconds.

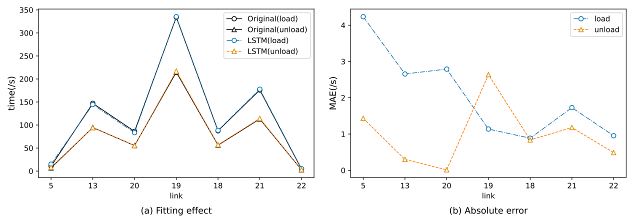

Fig. 6: Forecast results under heavy load and no load

As can be seen from Figures 4 to 6, changes in all three factors - weather, driver's behavior and truck load - can lead to varying degrees of change in travel time, so considering these three factors in the input features can further improve the prediction accuracy of the model, thus validating the need for open pit mine truck feature selection.

4 Visualization of Truck Travel Time Prediction Model in Open-Pit Mine

The visualization system of truck travel time prediction model in the open-pit mine is mainly divided into two parts: travel time prediction model and three-dimensional road network topographic map. The former uses Libtorch to invoke the LSTM neural network model in Pytorch to build a visualization system of truck travel time prediction model in the open-pit mine. The latter uses the Qt extension tool in VS and OSG graphics engine to build a 3D road map visual system, and the two are combined to establish the complete prediction model visualization system.

The visualization system contains two functions: query function and display function. The query function is to predict truck travel time by inputting link parameters and calling the neural network model in the Qt query interface. The display function is mainly to display the road network structure of open-pit truck transportation on the 3D topographic map of the Qt display interface, and display the truck travel time of 24 links in the road network structure according to the results predicted by the neural network. Figure 7 shows the final visualization interface. On the left side of the interface, the travel time of 24 links in the road network structure can be viewed. In the middle of the interface, a three-dimensional topographic map of the surface mine is displayed, and on the right is the query interface.

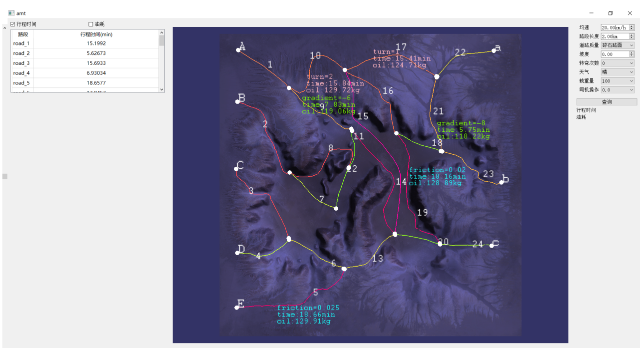

Fig. 7: Visualization interface

5 Conclusion

In order to achieve an accurate prediction of the travel time of open pit trucks, We fully analyzed the influencing factors affecting the travel characteristics of open pit trucks and extracted 11 features as input variables. The model is designed with the long short-term memory LSTM, and the accuracy of the LSTM prediction model is significantly improved compared with the traditional SVR and BP methods through experiments while revealing the changing trend of the open pit truck travel time and the error range of the prediction model under different weather, driver's behaviors, and load states. For the purpose of presenting the model prediction results, a 3D visualization platform of the open pit mine is created to visually display the truck travel times of the various links.

Although the LSTM is used to achieve good results for the prediction of truck travel time in the open pit mine, there are still areas that can be improved. For example, it can start from the overall spatial characteristics of the road network structure and consider all link information at the same time, rather than just the link information on the predicted path.

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