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Research Article

The Use of a Machine Learning Method to Predict the Real-Time Link Travel Time of Open-Pit Trucks

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Accurate truck travel time prediction (TTP) is one of the critical factors in the dynamic optimal dispatch of open-pit mines. This study divides the roads of open-pit mines into two types: fixed and temporary link roads. The experiment uses data obtained from Fushun West Open-pit Mine (FWOM) to train three types of machine learning (ML) prediction models based on *k*-nearest neighbors (kNN), support vector machine (SVM), and random forest (RF) algorithms for each link road. The results show that the TTP models based on SVM and RF are better than that based on kNN. The prediction accuracy calculated in this study is approximately 15.79% higher than that calculated by traditional methods. Meteorological features added to the TTP model improved the prediction accuracy by 5.13%. Moreover, this study uses the link rather than the route as the minimum TTP unit, and the former shows an increase in prediction accuracy of 11.82%.

1. Introduction

At present, shovel-truck systems (STSs) are commonly used in open-pit mining operations [1–3], especially for large open-pit mines. This is because STSs do not require extensive infrastructure in conjunction with a high mining intensity [4]. Although the trucks are very flexible, with a strong climbing ability, they also consume a large amount of fuel [5]. Related statistics showed that STSs contribute 50% of the operating costs in open-pit mines [6]. Therefore, almost all large open-pit mines are trying to optimize truck dispatching to achieve lower costs and higher mining efficiency [7–10].

Many open-pit mines have begun to use an open-pit automated truck dispatching system (OPATDS) in recent decades [9, 11]. Mining efficiency has increased through the integration of some truck dynamic dispatching principles (TDDPs) into the OPATDS [9, 11, 12]. The TDDPs rely heavily on an accurate truck cycle time [7, 8, 10], and one of its fundamental techniques is predicting the travel time of the trucks [11–14].

Several researchers have been working on travel time prediction (TTP) for open-pit trucks (OPTs) for many years. Sun [15] first defined the average value for the predicted travel time of a truck based on artificial statistical data. However, the travel time is influenced by many factors, including truck type, load status, road properties, and weather conditions, making it difficult to predict the average travel time accurately and efficiently.

Run-cai [16] used an artificial neural network (ANN) to predict the travel time of OPTs. Considering the randomness of TTP, they took several factors, namely, road conditions, truck type, and truck load status, into consideration. A total of 336 data records were used in their ANN model, and the results were better than those obtained using manual statistical methods.

Jiangang [17] proposed a real-time dynamic TTP model based on the adaptive network-based fuzzy inference system (ANFIS) and discussed the theory and method of the ANFIS network. The ANFIS is a hybrid learning algorithm consisting of an error backpropagation algorithm, which performs with a higher calculation speed and better accuracy than the ANNs used in [16].

Chanda and Gardiner [18] compared the predictive capability of three truck cycle time estimation methods, that is,

Table 1: Summary of the current state of TTP for OPTs.

Year	Authors	Methods	Conclusions	Ref.
1998	Sun	Manual statistics	An available method	[15]
2005	Run-cai	ANNs	Better than [15]	[16]
2005	Jiangang	ANFIS	Better than [16]	[17]
2010	Chanda and Gardiner	ANNs, MRs, and TALPAC	Each has its advantages	[18]
2010	Xue et al.	LS-SVR	An available method	[21]
2013	Edwards and Griffiths	MRs and ANNs	ANN is better than MR	[19]
2013	Erarslan	A computer-aided system	An available method	[20]
2014	Meng	BP-ANNs and SVM	SVM is better than BP-ANN	[22]

computer simulation, ANN, and multiple regression (MR), in open-pit mining using TALPAC software and MATLAB. The results indicated that both the ANN and MR models showed better predictive abilities than the TALPAC model, which usually overestimated the travel time of longer haul routes while underestimating that of shorter haul routes. However, the difference between the time predicted by these two methods and the realistic travel time was insignificant.

Edwards and Griffiths [19] attempted to predict the travel time of open-pit excavators through the development of ESTIVATE. Initially, ESTIVATE utilized a MR equation to predict the time, although it failed to provide an adequately robust predictor. Subsequently, improvement to ESTIVATE's predictive capacity was sought through the use of ANNs, which provided a significant improvement over the MR approach.

Erarslan [20] focused on the truck speed and developed a computer-aided system to estimate the speed data for different resistances. Then, the truck travel time was equivalent to the length of the road divided by the truck speed.

Considering the various influencing factors on TTP, Xue et al. [21] proposed a dynamic prediction method that comprised an ensemble learning algorithm using least squares support vector regression (LS-SVR). The results obtained from the MATLAB model showed the effectiveness and high accuracy of their algorithms.

Meng [22] compared the support vector machine (SVM) approach with the backpropagation (BP) algorithm and observed that the SVM model performed with a higher accuracy than the BP neural network model in TTP.

Reported studies on the TTP of OPTs are summarized in Table 1. Several aspects of the table require further discussion:

(1) Most of the existing studies have considered open-pit roads as a single category. Unlike urban traffic networks, there are many temporary roads in open-pit mines, for example, coal mines in Kuzbass, where temporary roads constitute up to 80% of the total road length [23]. A TTP model based on commonly fixed roads may not be reliable because the temporary roads between load and dump points change frequently.

(2) Most experiments reported in the literature were based on the route travel time prediction (RTTP), although the number of routes from A to B exceeds one. Thus, the RTTP with uncertainty must be improved.

(3) Reported studies have seldom considered the meteorological factors when the open-pit mine is extracting. For example, snow or heavy rain decreases the speed of trucks and has an adverse effect on the travel time of vehicles [24–27].

(4) Available predictive models have been based on small-scale datasets; for example, only hundreds of data records were used in [15–17, 21]. Better results are usually obtained when using large-scale training datasets.

With the rapid development of machine learning (ML) and big data technology, the TTP of OPTs is expected to become faster and more accurate. In this study, the primary objectives and improved measures are as follows:

(1) The open-pit mine roads are divided into two types: long-term fixed roads and temporary roads. Experiments explore the results of TTP on the two different types of roads.

(2) This paper uses the link rather than the route as the minimum prediction unit. The difference between the link and route is that the route contains multiple road nodes. Independent TTP models are used to train each link road instead of using the same TTP model for the entire road network.

(3) The experiments in this paper explore the impact of meteorological conditions on TTP, which means meteorological features are added to the model training process.

(4) The OPATDS database stores a large amount of truck condition data. For large-scale data, machine learning methods tend to have good prediction performance. More than a million records are used to train the link travel time prediction (LTTP) model in this study.

2. Models and Experiments

2.1. Experimental Roadmap and Methods. As shown in Figure 1, Fushun West Open-pit Mine (FWOM, Fushun Mining Group Co., Ltd.) is located in Fushun city, Liaoning province,

FIGURE 1: Location of the Fushun West Open-pit Mine.

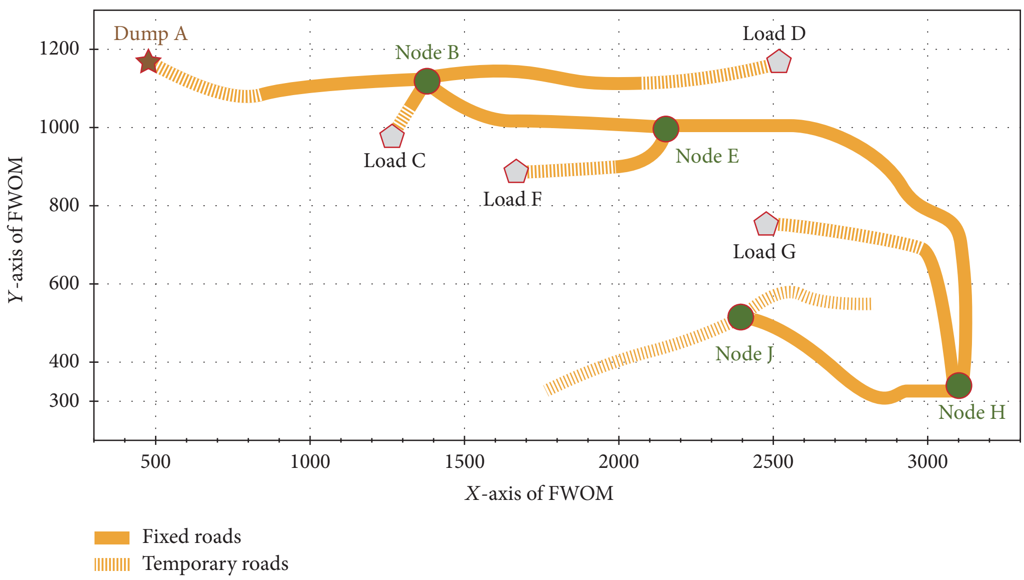

FIGURE 2: Experimental roadmap of the FWOM.

China, approximately 50 km east of Shenyang. The FWOM is the largest open-pit coal mine in Asia and produces an estimated 1.5 billion tons of coal [28].

The roadmap used in this experiment is shown in Figure 2, which is part of the road networks of the FWOM.

The nodes of transportation roads typically remain the same at a specified time, whereas roads to load points and dump points change with mining activities. According to the changing road nodes, link roads can be divided into two categories:

(1) Fixed link roads, for example, the link roads between node B and node E, node E and node H, and node H and node J.

(2) Temporary link roads, for example, the link roads between node B and node D, node E and node F, and node G and node H.

ML, which is a field of computer science, gives computers the ability to learn without being explicitly programmed [35, 36]. ML is related to computational statistics and suitable for predicting tasks because of its self-adaptation and self-feedback characteristics [37, 38]. An experimental flow chart used in the ML method is given in Figure 3. Note that the LTTP model of each experimental link road is independently trained.

Figure 3 shows the three steps of LTTP using ML. As the most crucial step, training the LTTP model consists of two parts: ML algorithms and training data. These two parts are indispensable because training the ML prediction models requires a large amount of data provided by the OPATDS. In the second step, LTTP model predictions are obtained from the test data, and the prediction performance of the model can also be evaluated. The final step involves modifying the parameters of the LTTP model until the result is acceptable. In particular, the test dataset is a dataset that is independent of the training dataset [39].

2.2. ML Algorithms Selection. ML tasks are typically classified into four broad categories [40]: supervised learning, unsupervised learning, reinforcement learning, and semisupervised

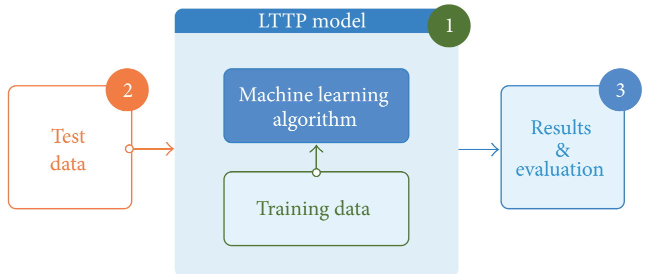

Figure 3: Experimental flowchart of ML methods.

Table 2: Adaptability analysis between ML algorithms and LTTP.

Algorithms	Adaptability analysis	Apply
ANNs	The effect has been thoroughly verified by many existing studies.	No
BNs	A probabilistic model that is not suitable for this study [29].	No
SVM	Perfect theoretical basis with high generalization ability [30].	Yes
RF	An ensemble learning method evolved from DT; better than DT [31].	Yes
LR	It solves the classification problems; not suitable for this study [32].	No
kNN	An efficient algorithm for the classification and regression tasks [33].	Yes
DT	RF has been chosen; there is no need to choose DT.	No
HM	A probabilistic model that is not suitable for this study [34].	No

learning [41]. The LTTP of OPTs belongs to the typical supervised learning task due to the labeled training data from the OPATDS [42]. Prediction models output the travel time values of OPTs, which can be considered to be a regression problem of supervised learning.

There are many ML algorithms that can be used to solve the regression problem of supervised learning, such as ANN, Bayesian network (BN), SVM, random forest (RF), logistic regression (LR), k-nearest neighbors (kNN), decision tree (DT), AdaBoost [43], and hidden Markov model (HM) approaches [44]. The adaptability analysis between LTTP and the various ML algorithms is given in Table 2. Based on the comparison results, this paper chooses the kNN, SVM, and RF algorithms to build the LTTP models of OPTs.

kNN is a nonparametric method used for classification and regression, and the kNN regression computes the mean of the function values of its k-nearest neighbors [33, 45]. The goal function regression $f_{\mathrm{kNN}}(x)$ of kNN regression is written as follows [45]:

$$f_{\mathrm{kNN}}(x) = \frac{1}{k} \cdot \sum_{i \in N_k(x)} y_i, \tag{1}$$

where x is an unknown pattern; $N_k(x)$ is the indices of the k-nearest neighbors of x; and y_i is the predicted labels.

The original SVM algorithm was invented by Cortes and Vapnik [46], and its efficiency in classification has been verified in many case studies [47]. The detailed introduction of SVM can be found in Smola and Schölkopf [48], in which they published the complete tutorial on support vector regression. To train the SVM regression model, the following must be solved:

$$\text{minimize} \quad \frac{1}{2}\|w\|^2 \tag{2a}$$

$$\begin{aligned} \text{subject to} \quad & y_i - \langle w, x_i \rangle - b \le \varepsilon \\ & \langle w, x_i \rangle + b - y_i \le \varepsilon, \end{aligned} \tag{2b}$$

where x_i represents the training features with target value y_i; $\langle w, x_i \rangle + b$ is the prediction value; and ε is a free parameter that serves as a threshold.

The RF algorithm evolved from DT theory and was created by Ho in 1995 [31]. This approach incorporates the bootstrap aggregating (Bagging) algorithm, which is a method for generating multiple versions of a predictor and then using these to obtain an aggregated predictor [49]. The RF method has a higher degree of efficiency and accuracy than the DT method because of Bagging.

2.3. Training Data Structure. The training dataset is the most critical factor when training ML prediction models, and it consists of several features and corresponding target values [50]. Many features commonly affect the LTTP of OPTs, which can be broadly classified into three categories: truck features, road features, and meteorological features. The meteorological features are considered in this paper because rainy and snowy weather reduces both the friction coefficient of roads and the truck driver's vision. According to the relevant statistics reported by the U.S. Federal Highway Administration, bad weather can lead to a 35% reduction in car speed [51].

Table 3: Preprocessed data for training the ML prediction models.

Date	Start time	Arrival time	Truck Id	Truck type
2017-03-01	16:23:20	16:26:57	202	BELAZ-L
2017-03-02	20:12:09	20:18:12	503	MT-86
Truck status	x-axis start	y-axis start	x-axis arrival	y-axis arrival
Run	1344	1188	2191	968
Run	2576	783	3095	327
Load status	Start node	Arrival node	Pressure (100 Pa)	Wind speed (m/s)
Empty	B	E	1002	1
Coal	G	H	999	0.6
Temperature (°C)	Relative humidity (%)	Precipitation (mm)	Rain	Travel time (hour:min:sec)
2	90	0	No	00:03:37
1	96	0	No	00:06:03

Table 4: Description of the variables used in the prediction.

Variables	Type	Role	Description
Truck Id	Numeric	Feature	The serial number of truck.
Truck type	Categorical	Feature	The type of the truck (i.e., BELAZ-L, BELAZ-M, and MT86).
Truck status	Categorical	Feature	The status of the truck (i.e., running, waiting, and stop).
x-axis start	Numeric	Feature	The x coordinate of the truck at the starting position.
y-axis start	Numeric	Feature	The y coordinate of the truck at the starting position.
x-axis arrival	Numeric	Feature	The x coordinate of the truck at the ending position.
y-axis arrival	Numeric	Feature	The y coordinate of the truck at the ending position.
Load status	Categorical	Feature	The load status of the truck (i.e., empty and coal).
Start node	Categorical	Feature	The node code of the starting position of the road.
Arrival node	Categorical	Feature	The node code of the ending position of the road.
Pressure	Numeric	Feature	A fundamental atmospheric quantity.
Wind speed	Numeric	Feature	A fundamental atmospheric quantity.
Temperature	Numeric	Feature	A fundamental atmospheric quantity.
Relative humidity	Numeric	Feature	A fundamental atmospheric quantity.
Precipitation	Numeric	Feature	A fundamental atmospheric quantity.
Rain	Categorical	Feature	A fundamental atmospheric quantity (i.e., yes and no).
Travel time	Date time	Target	The travel time of the truck on each link.

The data used in the following experiments originate from the FWOM. The truck and road feature data are from the OPATDS, while the weather data are collected from the China Meteorological Administration (CMA) Number 54351 monitoring station. The preprocessed training dataset samples in this experiment are listed in Table 3. There are 16 variables serving as the features, and the target is the truck travel time. Table 4 shows the description of the target and each feature used for the prediction in this study.

2.4. Program and Pseudocode. This study used sophisticated algorithms to predict the link travel time in open-pit mines, and the three ML algorithms in the prediction models were based on scikit-learn, which is an open-source ML module in the Python programming language [52, 53]. The pseudocode of the methodology in this study is illustrated in Figure 4.

3. Results and Discussion

3.1. Predictions of the ML Models. For the training datasets, 2,246,746 historical records from March 2017 were exported from the OPATDS database of the FWOM. After data preprocessing, the structure of the training data was similar to those in Table 3. The experimental parameters encompassed one type of link road trained by three different ML algorithms (kNN, SVM, and RF) resulting in 18 LTTP models. The prediction results for the last 50 records of the test datasets are shown in Figure 5.

```python
# Import required modules
import pandas as pd
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split

# Load preprocessed dataset
dataset = pd.read_sql("Preprocessed Dataset")
features = dataset['Features']
target = dataset['Target']

# Split train dataset(70%) and test dataset(30%)
features_train, features_test, target_train, target_test = train_test_split(
    features, target,
    test_size=0.3,
    random_state=50
)

# Define models and parameters
SVR_Model = SVR(
    gamma='auto',
    kernel='rbf'
)
KNN_Model = KNeighborsRegressor(
    algorithm='auto',
    metric='minkowski',
    n_neighbors=10
)
RF_Model = RandomForestRegressor(
    bootstrap=True,
    criterion='mse',
    max_features='auto'
)

# Training models and prediction
for model in [SVR_Model, KNN_Model, RF_Model]:
    model.fit(features_train, target_train)
    model.predict(features_test)
    model.score(features_test, target_test)
```

Figure 4: The pseudocode of the ML methodology.

To derive the best LTTP model for each link road, the aforementioned prediction results were evaluated based on the mean absolute deviation (MAD) and the mean absolute percentage error (MAPE) methods, which are commonly used for regression problem evaluation.

The MAD, as expressed in (3a), is a summary statistic of statistical dispersion or variability [54, 55]. The MAPE is a measure of the accuracy of a prediction method in statistics, as written in (3b) [56]. Because the MAPE is a percentage, it is often easier to understand than the other statistics. For example, if the MAPE is 5, on average, the forecast is off by 5% [57].

$$\text{MAD} = \frac{\sum_{i=1}^{n} \left| x_{\text{obs},i} - x_{\text{model},i} \right|}{n}, \tag{3a}$$

$$\text{MAPE} = \frac{\sum_{i=1}^{n} \left| \left(x_{\text{obs},i} - x_{\text{model},i} \right) / x_{\text{obs},i} \right|}{n} \times 100\,(\%), \tag{3b}$$

where $x_{\text{obs},i}$ represents the observation values; $x_{\text{model},i}$ represents the prediction values; and n is the number of data records.

Table 5 lists the MAD and MAPE values obtained from the three ML methods for each experimental link road.

Smaller MAD and MAPE values reflect better prediction performance of each LTTP model, and the smallest records are highlighted in Table 5. The results of the six experimental link roads indicate that the LTTP models built using the SVM and RF methods are better than those using the kNN algorithm. Table 6 summarizes the optimal ML prediction models for each link road.

The coefficient of determination, R^2, is widely used in statistical tests to evaluate the predictive capability of a model and is also used in this study. The R^2 value with one independent variable is written as follows [58]:

$$R^2 = \left[\frac{1}{N} * \sum \frac{(x_i - \overline{x}) * (y_i - \overline{y})}{\left(\sigma_x * \sigma_y \right)} \right]^2, \tag{4}$$

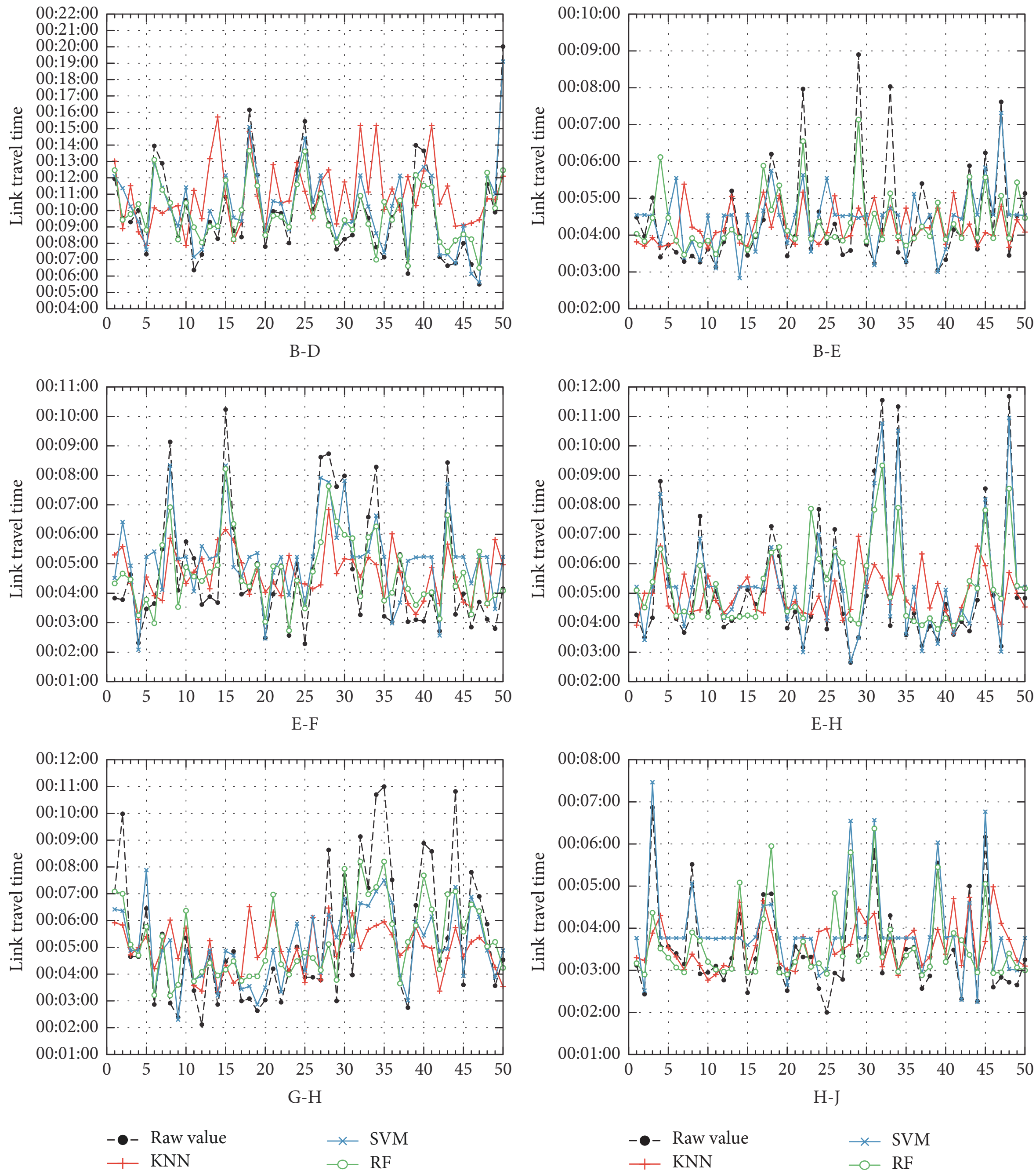

Figure 5: Prediction results for the different ML methods.

where N is the number of observations used to fit the model; $\overline{x}$ and $\overline{y}$ are the mean values of x and y, respectively; x_i and y_i are the values of observation i; and σ_x and σ_y are the standard deviations of x and y, respectively.

Table 7 shows the R^2 values of the three ML models for each link road. The R^2 values range from 0 to 1, and R^2 equal to 1 indicates perfect accurate prediction. There are some differences between Tables 6 and 7, that is, the optimal ML model of B-E, H-J, and G-H. However, the MAPE was still selected for choosing the optimal model because the R^2 value cannot be used to evaluate predictive errors.

3.2. Discussion of Traditional Averaging Methods and ML Models. To compare the LTTP of ML models and traditional averaging methods, controlled experiments were performed. The flow chart of traditional averaging methods is illustrated in Figure 6.

For each record in the test dataset, the experiments traced back the corresponding top 10, 20, 30, 40, and 50 records and then calculated the average value as the final prediction. To improve the accuracy of the traditional averaging methods, each calculation used only historical data for the same truck type and load status. The results obtained

Table 5: LTTP evaluation based on the different ML models.

Link road	Road type	Evaluation	kNN	SVM	RF
B-E	Fixed	MAD	5.91E − 04	5.09E − 04	**4.56E − 04**
		MAPE	1.78E + 01	1.58E + 01	**1.44E + 01**
E-H		MAD	9.44E − 04	**3.32E − 04**	6.37E − 04
		MAPE	2.49E + 01	**9.57E + 00**	1.81E + 01
H-J		MAD	5.16E − 04	3.55E − 04	**3.54E − 04**
		MAPE	2.14E + 01	1.59E + 01	**1.48E + 01**
B-D	Temporary	MAD	1.71E − 03	**5.44E − 04**	6.70E − 04
		MAPE	2.75E + 01	**8.09E + 00**	9.90E + 00
E-F		MAD	9.59E − 04	8.05E − 04	**5.63E − 04**
		MAPE	3.13E + 01	2.94E + 01	**1.82E + 01**
G-H		MAD	1.18E − 03	**7.35E − 04**	7.85E − 04
		MAPE	3.42E + 01	**1.94E + 01**	2.38E + 01

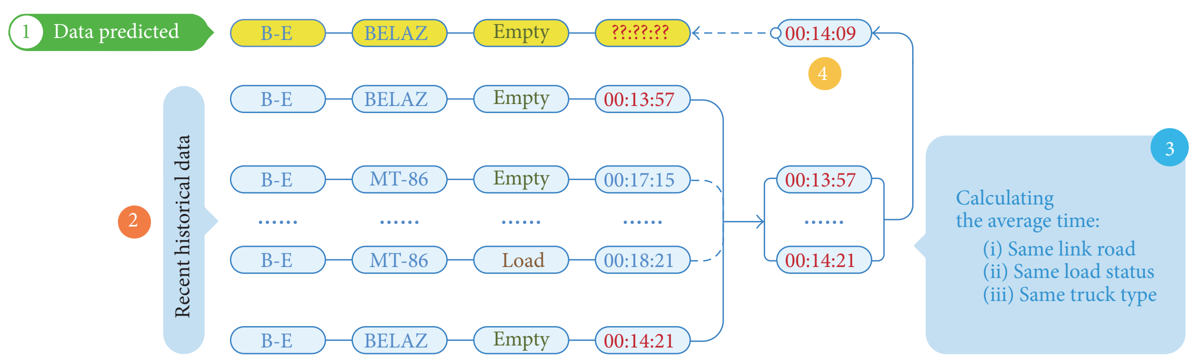

Figure 6: The flow chart of traditional averaging methods.

Table 6: Summary of the optimal ML prediction models for each link road.

Road	Type	Optimal ML model
B-E	Fixed	RF
E-H		SVM
H-J		RF
B-D	Temporary	SVM
E-F		RF
G-H		SVM

Table 7: R^2 values of the different ML models for each link road.

Road	SVM	KNN	RF	Optimal ML model
B-E	0.28	0.16	0.41	SVM
E-H	0.83	0.16	0.67	SVM
H-J	0.72	0.13	0.56	SVM
B-D	0.89	0.23	0.7	SVM
E-F	0.54	0.24	0.73	RF
G-H	0.61	0.19	0.62	RF

from the traditional averaging methods are summarized in Table 8.

Smaller MAD and MAPE values mean better prediction performance of the traditional averaging methods, and the smallest records are highlighted in Table 8. The predicted values obtained from the optimal ML method and a traditional average method for each link road are given in Table 9; the decrease in the MAPE is also shown.

Table 9 shows that the tested ML models are superior to the traditional averaging method in the context of LTTP because the former has smaller MAPEs. An average increase of 15.79% in prediction accuracy is achieved in all experimental link roads, in which increases of 12.54% and 19.30% for three fixed and three temporary roads, respectively, are also obtained.

3.3. Discussion of Meteorological Features. This study also considered the influence of meteorological features on the LTTP of an open-pit mine. The data were obtained from a CMA monitoring station, including 5 variables: pressure, wind speed, temperature, relative humidity, and precipitation.

The Pearson correlation coefficient (PCC), an evaluation method developed by Pearson [59], was used to evaluate the linear correlation between two variables. The expression of the PPC is as follows:

$$\rho_{X,Y} = \frac{\operatorname{cov}(X,Y)}{\sigma_X \sigma_Y}, \quad (5)$$

Table 8: Results obtained from the traditional averaging methods.

Road	Evaluation	Traditional averaging methods 10 records	20 records	30 records	40 records	50 records
B-E	MAD	$1.02E-03$	$9.49E-04$	$9.17E-04$	$9.18E-04$	**9.04E − 04**
	MAPE	$3.06E+01$	$2.81E+01$	$2.66E+01$	$2.64E+01$	**2.58E + 01**
E-H	MAD	$1.22E-03$	$1.13E-03$	$1.09E-03$	$1.09E-03$	**1.07E − 03**
	MAPE	$3.29E+01$	$3.00E+01$	$2.84E+01$	$2.81E+01$	**2.73E + 01**
H-J	MAD	$6.29E-04$	$6.09E-04$	$5.87E-04$	$5.81E-04$	**5.80E − 04**
	MAPE	$2.54E+01$	$2.47E+01$	$2.36E+01$	$2.34E+01$	**2.33E + 01**
B-D	MAD	$2.15E-03$	**1.83E − 03**	$2.46E-03$	$2.36E-03$	$2.05E-03$
	MAPE	$3.17E+01$	**2.69E + 01**	$3.86E+01$	$3.62E+01$	$3.25E+01$
E-F	MAD	$1.16E-03$	**1.10E − 03**	$1.14E-03$	$1.15E-03$	$1.16E-03$
	MAPE	$3.91E+01$	**3.63E + 01**	$3.81E+01$	$3.90E+01$	$3.95E+01$
G-H	MAD	**1.29E − 03**	$1.38E-03$	$1.36E-03$	$1.32E-03$	$1.30E-03$
	MAPE	**4.04E + 01**	$4.12E+01$	$3.91E+01$	$3.70E+01$	$3.57E+01$

Table 9: Comparison between the optimal ML model and the optimal averaging method.

Road	Type	Optimal average method (MAPE)	Optimal ML model (MAPE)	MAPE decrease	Average
B-E	Fixed	$2.58E+01$	$1.44E+01$	11.40%	12.54%
E-H		$2.73E+01$	$9.57E+00$	17.73%	
H-J		$2.33E+01$	$1.48E+01$	8.50%	
B-D	Temporary	$2.69E+01$	$8.09E+00$	18.81%	19.30%
E-F		$3.63E+01$	$1.82E+01$	18.10%	
G-H		$4.04E+01$	$1.94E+01$	21.00%	
Average					15.79%

Table 10: Prediction results after including meteorological data.

Type	Road	Methods	Meteorological features	MAD	MAPE	MAPE decrease (no-yes)%
Temporary	B-E	RF	No	$6.90E-04$	$2.07E+01$	6.30%
			Yes	$4.56E-04$	$1.44E+01$	
	E-H	SVM	No	$3.41E-04$	$1.69E+01$	7.28%
			Yes	$3.32E-04$	$9.57E+00$	
	H-J	RF	No	$4.16E-04$	$1.86E+01$	3.80%
			Yes	$3.54E-04$	$1.48E+01$	
Fixed	B-D	SVM	No	$6.35E-04$	$1.22E+01$	4.08%
			Yes	$5.44E-04$	$8.09E+00$	
	E-F	RF	No	$6.60E-04$	$2.17E+01$	3.50%
			Yes	$5.63E-04$	$1.82E+01$	
	G-H	SVM	No	$8.42E-04$	$2.52E+01$	5.80%
			Yes	$7.35E-04$	$1.94E+01$	
Average						5.13%

where $\mathrm{cov}(X, Y)$ is the covariance; σ_X is the standard deviation of X; and σ_Y is the standard deviation of Y.

The PPC values of different variables are shown in Figure 7, including the 5 meteorological variables and truck travel time. A high PCC value indicates a closer relationship between the two variables.

Following controlled experiments, the effect of meteorological features was investigated by adding or removing individual features. We selected the optimal ML model for each link road. The raw (observation) values and predicted results with/without meteorological features are shown in Figure 8.

The results of the controlled experiments are shown in Table 10; the calculated decrease in the MAPE is also shown. The results considering meteorological features are better than those without meteorological features. The MAPE decreased by 5.13% on average for all link roads after adding the meteorological data.

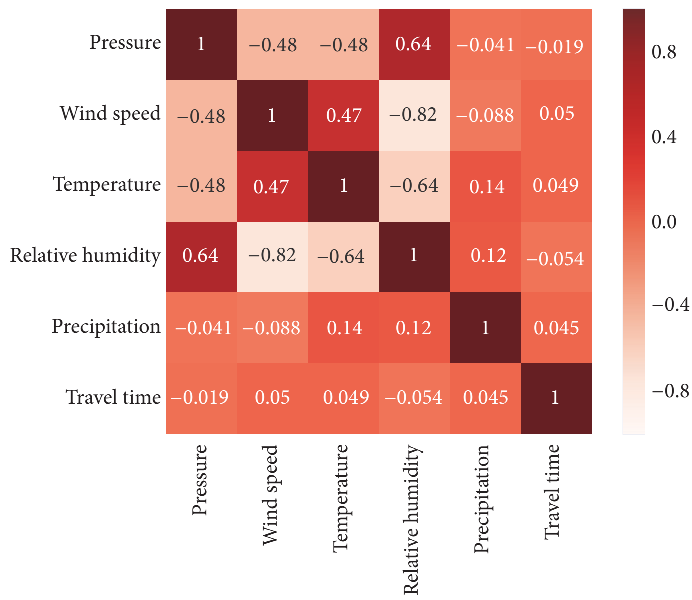

Figure 7: The PCC heat map of meteorological features.

Table 11: Evaluation of LTTP based on different ML models.

Link road	Road type	Evaluation	kNN	SVM	RF
A-B	Fixed	MAD	$4.95E-04$	$3.28E-04$	**2.99E − 04**
		MAPE	$4.69E+01$	$3.40E+01$	**3.36E + 01**

3.4. Discussion of LTTP and RTTP. The above experiments used the link rather than the route to predict the travel time of OPTs. However, the differences between LTTP and RTTP need to be further discussed. In the ensuing discussion, the longest route between dump point A and load point G is selected, as shown in Figure 9.

The A-G route consists of 4 links: A-B, B-E, E-H, and H-G. Among them, the optimal ML prediction models of B-E, E-H, and H-G are SVM, RF, and SVM, respectively. The same experimental procedure as used in Section 3.1 was used to obtain the optimal ML model for A-B, and Table 11 shows the MAD and MAPE values of the three ML methods. It can be seen that the RF model is the best ML method for link A-B.

The SVM and RF methods are used to predict the RTTP of A-G because those two models have a good prediction performance. Thus, the experiments are summarized as follows:

(i) RTTP (SVM): using the SVM algorithm to train the TTP model for the route A-G.

(ii) RTTP (RF): using the RF algorithm to train the TTP model for the route A-G.

(iii) LTTP: using the optimal ML model for each link, that is, A-B (RF), B-E (SVM), E-H (RF), and H-G (SVM), and the truck travel time of A-G is the sum of each LTTP result.

Raw values and predicted results of the above three experiments are shown in Figure 10, while the evaluated results of those experiments are shown in Table 12. Both the MAD and MAPE values of the LTTP approach are smaller than the two RTTP methods. Thus, using the link as the prediction unit is better than using the route.

Table 12: Evaluation of the results between LTTP and RTTP.

Method	Model	Evaluation	Values
RTTP	SVM	MAD	$1.55E-03$
		MAPE	$2.08E+01$
RTTP	RF	MAD	$1.78E-03$
		MAPE	$2.35E+01$
LTTP	Assemble	MAD	**8.34E − 04**
		MAPE	**8.98E + 00**

4. Conclusions

The link roads of an open-pit mine are divided into fixed and temporary roads in this paper. Three ML algorithms, that is, kNN, SVM, and RF, are used for the LTTP of OPTs. The experimental results not only reflect the self-adaptive and self-feedback characteristics of the ML algorithms but also demonstrate the practicality of the method for road segments. The conclusions based on the results are as follows:

(1) LTTP models based on ML are more efficient and accurate than traditional averaging methods. An overall average increase of 15.79% in the prediction accuracy is obtained for six experimental link roads.

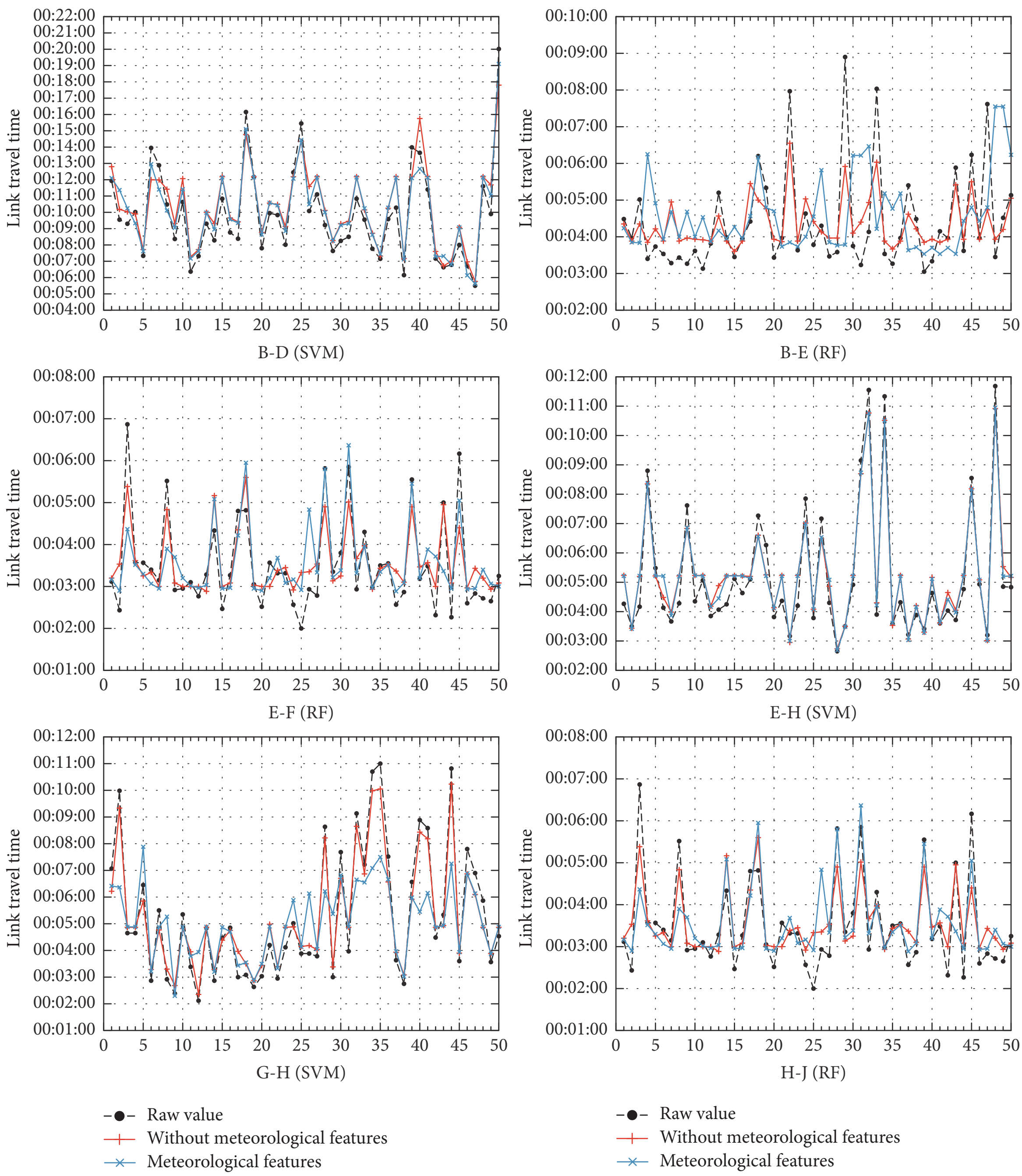

Figure 8: Comparison forecast results including and excluding meteorological features.

For temporary roads, the average accuracy increases by 19.30%.

(2) LTTP models established using the SVM and RF algorithms are better than those established using the kNN approach. There is no large difference between the SVM and RF results, although the RF algorithm requires less space and time complexity than the SVM algorithm.

(3) This paper is original in that it considers the effect of meteorological features on LTTP. The results show that considering the effect of meteorological features on LTTP increases the prediction accuracy by 5.13%.

(4) The differences between LTTP and RTTP are also discussed, and the former has a higher prediction accuracy. The MAPE decreases by 11.82% for the LTTP method.

Some work is already underway to incorporate the ML prediction models into the OPATDS of the FWOM, which will be helpful in improving the dispatching efficiency of the OPTs.

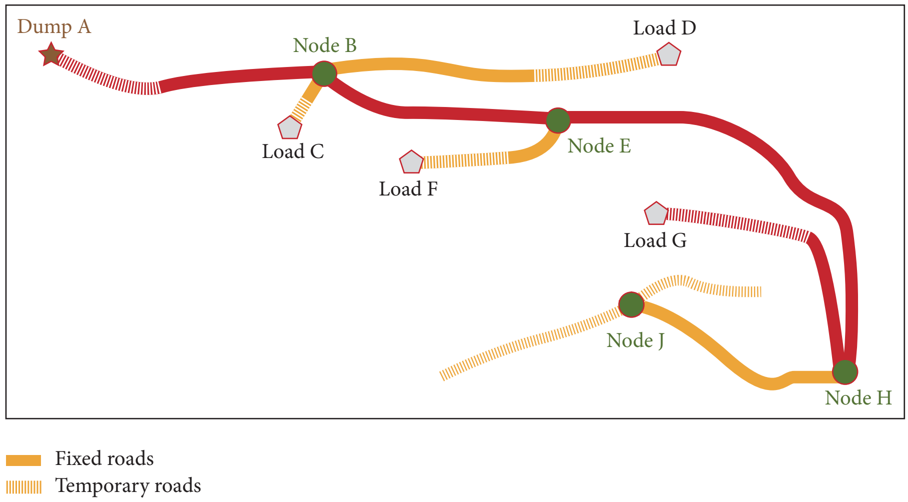

Figure 9: The location of the route A-G in the FWOM roadmap.

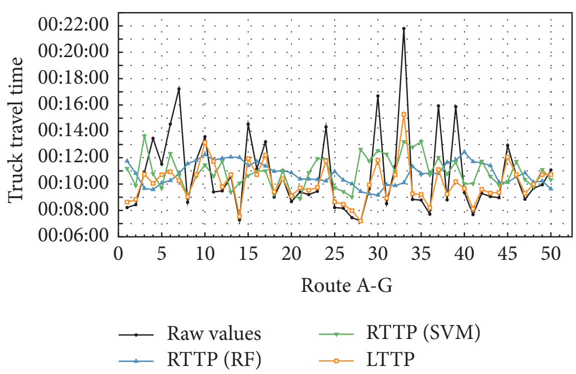

Figure 10: Prediction results for RTTP (RF), RTTP (SVM), and LTTP.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

Authors' Contributions

Xiaoyu Sun, as the principal investigator, provided the data used to train the ML models. Hang Zhang performed the experiments and wrote the paper. Fengliang Tian contributed the programming. Lei Yang proofread the manuscript.

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