Road surface friction prediction using long short-term memory neural network based on historical data

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ABSTRACT

Road surface friction significantly impacts traffic safety and mobility. A precise road surface friction prediction model can help to alleviate the influence of inclement road conditions on traffic safety, Level of Service, traffic mobility, fuel efficiency, and sustained economic productivity. Laboratory-based methods were used in most previous studies related to road surface friction prediction model development which are difficult for practical implementations. Moreover, for the existing studies about data-driven method development, the time-series features of road surface friction have not been considered. Thus, to utilize the time-series features of road surface friction for predictive performance improvements, this study employed a Long-Short Term Memory (LSTM) neural network to develop a data-driven road surface friction prediction model. According to the experiment results, the proposed prediction model outperformed the other baseline models in terms of three metrics. The impacts of the number of time-lags, the predicting time interval, and adding other relative variables as training inputs on predictive accuracy were investigated in this research. The findings of this study can support road maintenance strategy development, especially in winter seasons, thus mitigating the impact of inclement road conditions on traffic mobility and safety.

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Introduction

Road surface condition has a great impact on road traffic mobility and safety (Chen et al., 2017; Pisano, 2017; Shi & Fu, 2018; Strong et al., 2010; Z. Ye et al., 2009). Especially in winter season, terrible road surface conditions could result in more traffic crashes and low level of service (LOS). The United States spends $2.3 billion annually to keep highways clear of snow and ice; in Canada, winter highway maintenance costs more than $1 billion (Shi, 2010). Improving road surface condition monitoring systems and operations could result in fewer crashes, higher LOS, improved mobility, better fuel economy and sustained economic productivity (Rita, 2018). As one of the direct measurements of road surface condition, road surface friction has strong correlation with traffic accident risk (Wallman & Åström, 2001). Thus, to mitigate the impact of road surface condition on traffic safety and mobility, an efficient and cost-effective road surface friction prediction methodology is needed for these concerns.

Most previously prediction models for road condition related parameters predicting are developed based on laboratory tests. Shao et al. proved that the ice hazard only happened under both conditions based on field test data from seven countries (Shao et al., 1996). They also tried to predict the ice condition based on air temperature, wind speed and precipitation. However, the results showed great differences on different roadways. Samodurova (Samodurova, 2002) pointed out that the ice point varies in terms of the pavement types. Most ice prediction models are developed based on laboratory tests, and many significant factors are found to be related to ice generation. For example, Mohseni and Symons (Mohseni, 1995), and Diefenderfer et al. (Diefenderfer et al., 2006) both regressed the relationship between pavement temperature and various environmental conditions, such as illumination, air temperature, longitude, latitude etc., but the impact of these factors is still unmeasurable. Thus, based on the existing models which were built...
by laboratory tests, the precise road surface condition is hardly to be predicted.

Furthermore, several sensing technologies were developed for winter road surface condition monitoring. DSC-111 and DST-111 sensors are two remote optical sensors developed by Vaisala company (Ewan et al., 2013; Feng & Fu, 2008; Z. Ye et al., 2012). DSC-111 can provide the road surface state (dry, moist, wet, icy, snowy/frosty or slushy) based on the backscattered signals of infrared light and can measure the friction level of the road surface and DST-111 can present the pavement surface temperature, air temperature and relative humidity by long wave infrared radiations detection (Pilli-Sihvola et al., 2006). Previous studies demonstrated DSC-111 can provide accurate surface state measurement, but the friction detection of DST-111 is not precise (Feng & Fu, 2008). Road Condition Monitor (RCM) 411 is an optical instrument equipped with a transmitter to send a probe light pulse and a detector to measure the back scattered light, which can be easily installed to a passenger vehicle (Haavasoja et al., 2012). Existing researches conducted experiments to demonstrate that the RCM-411 is accurate in temperature, water thickness and road surface status detection (Fay et al., 2018; Haavasoja et al., 2012; Maenpaa et al., 2013). For friction detection, even when the detected friction value does not always accurately match the actual friction, it still can be adjusted to the actual friction value based on calibration methods (Haavasoja et al., 2012). Such sensing technologies have already been employed for real-time road monitoring implementations, e.g. Road Weather Information Station (RWIS) in US and etc. (Boselly et al., 1993; Fetzer et al., 2018; Karsisto & Nurmi, 2016; Maenpaa et al., 2013; Saarikivi, 2012; Singh et al., 2017). However, each sensing technology has its own disadvantages, e.g. fixed sensor can only cover a fixed area, and using mobile sensors is time and energy consuming. Therefore, how to utilize the data collected by such sensing technologies for expanding ability and predicting the road surface condition would be valuable for improving the effectiveness and efficiency of the whole system.

By utilizing the data collected by existing sensing technologies, several researchers have developed data-driven prediction models for road surface condition related parameters forecasting. Liu developed a road surface temperature prediction model based on gradient extreme learning machine boosting algorithm (Liu et al., 2018). Solol developed a road surface temperature prediction model based on energy balance and heat conduction models (Sokol et al., 2017). In addition, some researchers developed road surface condition recognition algorithms based on computer vision technologies (Choi et al., 2010; Pan et al., 2018; Jonsson et al., 2014; Linton & Fu, 2016; Sukuvaara & Nurmi, 2012). However, previous studies have several disadvantages in terms of the prediction effectiveness. For example, those methodologies can only regress the current road surface condition based on current environmental measurements, e.g. air temperature, etc. They are not able to predict road surface condition in the future. Moreover, researches in the past demonstrated the existence of the time-series features of road surface condition (Kangas et al., 2013). However, only a few studies shed light on the time-series prediction model development. Thus, a prediction method which considers the time-series features of road surface condition is needed based on the above analysis.

Long-short term memory neural network (LSTM) is a kind of computational intelligence approach for dealing with time-series data (Cui et al., 2020b; Hochreiter and Jürgen Schmidhuber 1997; Li et al., 2019; Pu, Cui, et al., 2020b; Qiao et al., 2013). Previously, several studies demonstrated LSTM is more accurate in short-term prediction problems, e.g. traffic flow prediction, patient visitation frequency prediction, than other machine learning approaches, including random forest (RF) (Pu, Li, Ke, et al., 2020) and support vector regression (SVR) (Albousefi et al., 2017) due to the ability of handling both long-term and short-term dependencies. Based on the above considerations, the primary objective of this study is to develop a road surface friction prediction model based on LSTM NN model using historical data. The RCM-411 friction sensing data were selected as the historical data set due to the accurate sensing results. To evaluate the predictive effectiveness of the proposed method, several baseline prediction models were employed for the comparison purpose. Besides evaluating the overall prediction performance evaluation, the impacts of the number of time-lags, the influence of the time interval between each time-step and the influence of adding additional features were also evaluated. The findings of this study can help to mitigate the impact of road surface condition on road traffic safety and mobility, especially in winter seasons.

Data

Testing field

The data used in this study were collected by the on-vehicle RCM 411 sensor on European route E75 from Sodankylä to Kemi in Finland. The total length of the
road for the data collection is 186 miles. In winter season, from October to next April, the air temperature is historically relatively low in this area. The lowest air temperature could be negative 40 Celsius, and the average minimum air temperature is about negative 15 Celsius. The average maximum air temperature is still under the ice point of water. In other seasons, the air temperature is not as high as in normal areas. The historical average maximum air temperature in July is about 20 Celsius. July is the month with the highest temperature in this area. Therefore, the study field has issues caused by cold weather. There was a vehicle equipped with an RCM 411 sensor for road surface friction data collection since February 2017. In addition, various road surface condition related parameters were detected as well, e.g. calculated road surface status, water thickness, air temperature, etc., the detailed information is presented in the next section. Figure 1 shows the distribution of calculated road surface status of two selected days, one is in winter season and another one is in summer season. Basically, there are five calculated road surface status, including dry, moist, slush, ice, and snow or hoar frost. In the figure, calculated road surface status is varied along the road for both tow selected days. The most part of the road is covered by snow or hoar frost in winter season, while the most part of the road is dried in summer season.

Data description

The historical data collected by RCM 411 sensor covers 446 days from February 17th, 2017 to May 9th, 2018. During the data collection time-period, the vehicle equipped with the RCM 411 sensor drove through the testing field at least once per day, so that every point on the road has at least one friction record for every single day. In this study, it is assumed that no spatial correlation of the road surface friction exists for adjacent road segments. Thus, the testing field was separated into road segments based on the calculated road surface status of the RCM 411 sensor. The road segmentation methodology will be introduced in the next section.

As mentioned in the section of Introduction, RCM 411 sensor can provide accurate calculated road surface status, air temperature data, road surface friction data and road surface water thickness data. In most cases, road surface status is defined or measured based on the friction information, since the friction is directly related to the traffic safety. In addition, the road surface friction coefficient is the most important indicator to characterize its anti-sliding performance.
which is an important indicator of the road safety quality. A stable road surface friction coefficient can provide a safety reserve for driving, thus reducing the possibility of traffic accidents occurrence. Therefore, the road surface friction is selected as the representative of the road surface condition in this study. Historical road surface friction data was used as the input of the proposed prediction model for predicting the road surface friction value in future time periods. Other road condition related variables, like road surface water thickness, air temperature and road surface temperature will also be used as the input of the prediction model for testing if they can improve the accuracy the proposed prediction model.

Methodology

Road segmentation

Road segmentation is the prerequisite for the prediction of road surface condition. Generally, the adjacent road segments share similar properties, but the distant sections are inclined to be different from each other. As mentioned in section of Testing Field, the whole distance of the study site is about 186 miles, and the calculated road surface status varies along with the road from dry to snow. The main objective of road segmentation is to guarantee that only one status exists within each road section during the testing time-period. To make the prediction model comparable, the length of each segment should be the same. In this paper, we proposed a spatial clustering method based on the K-means clustering algorithm. K-means clustering partitions \( n \) observations into \( k \) clusters in which each observation belongs to the cluster with the nearest calculated road surface status. We used the spatial distance calculated by Haversine formula to describe the distance function instead of Euclidean distance, as shown in Eq. (1).

\[
\begin{align*}
    d &= 2r \text{arcsin} \\
    &= \sqrt{\sin^2\left(\frac{\varphi_2 - \varphi_1}{2}\right) + \cos(\varphi_1) \cos(\varphi_2) \sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}
\end{align*}
\]

where \( d \) represents the spatial distance, \( r \) is radius of the earth, \( \varphi_1, \varphi_2 \) are the latitude of two points in radians, and \( \lambda_1, \lambda_2 \) are the longitude of two points, in radians.

Road surface friction prediction using LSTM NN

A Long-short Term Memory (LSTM) neural network is proposed to predict the short-term road surface friction due to its ability to handle both long-term and short-
term dependencies (Bengio et al., 1994; Sundermeyer et al., 2012). LSTM shares similar architecture with traditional Recurrent Neural Networks (RNN), which are composed of one input layer, one hidden layer and one output layer. The main modification of LSTM compared to RNN architecture is the structure of hidden layer (Gers & Cummins, 1999). The structure of LSTM NN is shown in Figure 2, where (a) presents LSTM cell and (b) depicts the LSTM Network structure.

Typically, at each time iteration \( t \), the LSTM cell has the input layer, \( X_t \), the output layer, \( h_t \) and the hidden layer. By adding a cell state component, the LSTM cell is capable of handling long-term dependencies of sequence data. The previous output cell state, \( C_{t-1} \) and the current input cell state, \( C_t \) both affect the current output cell state, \( C_t \). Besides, a LSTM cell has three gates control the information to flow into and out of the cell state, which are the forget gate, the input gate and the output gate, denoted as \( f_t \), \( i_t \) and \( o_t \), respectively. The forget gate controls how much information from previous cell state should be forgotten by the current cell state. The input gate handles how much information from the current input layer flows into the current cell state. The output gate controls how much information from current cell state would be conveyed into the current output layer. They can be calculated by the following equations,

\[
    f_t = \sigma_g(W_f X_t + U_f h_{t-1} + b_f) \tag{2}
\]

\[
    i_t = \sigma_g(W_i X_t + U_i h_{t-1} + b_i) \tag{3}
\]

\[
    o_t = \sigma_g(W_o X_t + U_o h_{t-1} + b_o) \tag{4}
\]

\[
    \tilde{C}_t = \tanh(W_C X_t + U_C h_{t-1} + b_C) \tag{5}
\]

where \( W_f, W_i, W_o \) and \( W_C \) are the weight matrices for mapping current input layer into three gates and current input cell state. \( U_f, U_i, U_o \) and \( U_C \) are the weight matrices for mapping previous output layer into three gates and current input cell state. \( b_f, b_i, b_o \) and \( b_C \) are bias vectors for gate and input cell state calculation. \( \sigma_g \) is the gate activation function which is normally a sigmoid function. \( \tanh \) is the hyperbolic tangent function which is the activation function for current input cell state.

Then, current output cell state and output layer can be calculated by following equations. Finally, the output of LSTM prediction model in this study should be the road surface friction in the next time iteration.

\[
    C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{6}
\]

\[
    h_t = o_t \cdot \tanh(C_t) \tag{7}
\]

Since it is assumed no spatial correlation between road segments, the spatial dimension of the input data is set as \( P = 1 \). The unit of time-step for road surface friction detection is set as 1-day, then, the dataset has 446 time-steps for each road segment. Suppose the number of the time-lag is set as \( T = t \) with \( L = l \) days between each time-lag, which means the model used the data in previous \( t \) consecutive time-steps to predict the road surface friction in \( t + 1 \) time-step. Then the dataset is separated into samples with \( t \) time-lags and the sample size is \( N = 446 - t \). Thus, each sample of the input data, \( X_t \), is a 2-dimensional vector with the dimension of \( [T, P] = [t, 1] \), and each sample of the output data is a single value. The input of the model for each road segment is a 3-dimensional vector which dimension is \( [N, T, P] = [446 - t, t, 1] \).

Before feeding into the model, all samples are randomly divided into training set, validation set and test set with the ratio 7:2:1. All prediction models share the same data structure. For training LSTM networks, the model was trained by minimizing the mean squared error with the batch size of 16 and learning rate of \( 10^{-5} \). The RMSProp was employed as the gradient descent optimizer with the alpha of 0.99 and the early stopping mechanism was utilized to avoid the overfitting.

**Predictive performance evaluation**

The performance of a LSTM NN in road surface friction prediction is compared to that of many classical baseline models for short-term prediction. Typically, ARIMA, Support Vector Regression (SVR), Bayesian Model (Ghosh et al., 2007; Pu, Li, Jiang, et al., 2020), Random forest (RF), Kalman filter, tree-based model and Feed-Forward NN were used for addressing short-term prediction problems (Guo et al., 2014; Wu et al., 2004; Chen et al.2016), e.g. traffic speed, travel time and crash severity prediction (Cui et al., 2020c, 2020; Ma et al., 2015; Zhang et al., 2018). However, several time-series prediction models were demonstrated that the predictive performance is not as accurate as others, e.g. ARIMA and Kalman filter. Therefore, based on previous research results, SVR, RF and Feed-Forward NN were selected for comparing the performance of road surface friction prediction with the proposed LSTM NN model in this study. Among these models, Feed-Forward NN, which is also called Multilayer Perceptron, is popular for precise performance in short-term prediction (Lv et al., 2014). RF and SVR are also well-known models for efficient predictive performance (Wu et al., 2004; Chen et al. 2016). For the parameters of model development, Radial Basis Function (RBF) kernel is deployed in SVR model. 10 trees were built, and there
was no preset limitation for maximum depth of the trees for the RF model. The Feed-Forward NN was composed of 2 hidden layers with 100 nodes in each layer.

Mean Absolute Error (MAE), Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE) are used as the measurements of predictive performance. The following equations present the measurement formulation.

\[
\text{MAE} = \frac{\sum_{i=1}^{N} |Y_i - \hat{Y}_i|}{N} \quad (8)
\]

\[
\text{MSE} = \frac{\sum_{i=1}^{N} (Y_i - \hat{Y}_i)^2}{N} \quad (9)
\]

\[
\text{MAPE} = \frac{100\%}{N} \sum_{i=1}^{N} \left| \frac{Y_i - \hat{Y}_i}{Y_i} \right| \quad (10)
\]

where \( N \) is the total number of samples in testing date set, \( Y_i \) is the ground truth of the road surface friction which is detected by RCM 411 sensor in this study, and \( \hat{Y}_i \) is the predicted road surface friction of the proposed prediction model. Typically, the MAE is used to measure the absolute error associated with a prediction, the MAPE presents a measure of the percentage of average misprediction of the model and the MSE measures the relative error for a prediction. The prediction model with the smaller values of MAE, MSE and MAPE performs better.

**Numerical results**

**Road segmentation**

As it follows from Eq. (1), a large \( K \) value lowers the size of each cluster, leading to insufficient data to train the LSTM model. In contrast, a small \( K \) value may result in the mixture of various types of status. Therefore, we proposed a heuristic method by slightly increasing the \( K \) and evaluating the degree of mixture of each cluster. However, it is practically impossible to ensure only one status existed in each segment. Even for the 100-meter road segment, there could be 1-meter section with other status, which is physically normal. Thus, the proportion between the outlier status and the normal status of each segment is used as an indicator (mixture rate), and the \( K \) is derived to guarantee the mixture rate below 15%. Finally, the \( K \) is calculated as 1487. Figure 3 visualizes the calculated road surface status of the randomly selected road segments on two days. Seen from the figures, even the
calculated road surface statuses are different, only one status exists within the selected road segments. After segmenting the road based on the proposed criteria, the average road surface friction could be used to represent the value of each road segment. Otherwise the value of the road surface friction within each road segments could vary a lot.

**Predictive performance evaluation**

The proposed LSTM NN model and other baseline models were trained based on the same training data set for each road segment separately, and the predictive performance for each model was calculated based on predicted values and the ground truth. In this step, only road surface friction in previous time-period was used as the model input. The final predictive performance measurements were the averaged value of all road segments. Table 1 shows the prediction performance comparison of the LSTM with other baseline models, and the values in the parentheses is the standard deviation of the predictive performance measurements. Among other algorithms, RF performed much better than SVR and Feed-Forward NN with MAE of 0.166, MSE of 0.0132 and MAPE of 16.6%, which makes sense due to the majority votes mechanism of RF model. The Feed-Forward NN had the worst predictive performance, which is caused by the sparsity of the data. The proposed LSTM model outperformed all models with MAE of 0.0778, MSE of 0.0112 and MAPE of 15.16%, which indicates the best performance in predicting road surface friction by only consider the road surface friction in previous time-period.

To further examine the predictive performance of the proposed LSTM model in a more intuitive way, the comparison of ground truth and the predicted values of the LSTM on multiple randomly selected days for all road segments were visualized in Figure 4. For the most of road segments, the predicted values were very close to the observed data. Only a few of the road segments had clear errors in road surface condition prediction. Overall, the LSTM effectively predicted road surface friction based on historical road surface friction data for all road segments.

### Evaluating the influence of number of Time-Lags on predicting accuracy

The number of time-lags is the temporal dimension of the input data, which might influence the prediction performance of the proposed LSTM model. Intuitively, the more time-lags will convey temporal features in longer time-period, and the LSTM will learn more features in previous time periods. In order to explore the influence of the number of time-lags, the LSTM was trained by the data sets with different number of time-lags, from 1 to 10 separately, for all road segments. All data samples had the same time interval (1-day) between time-lags. Table 2 shows the average predictive performance of the proposed LSTM models which were trained by the data sets with different number of time-lags.

It is noticed that all three measurements (MAE, MSE and MAPE) gradually dropped from the number of time-lags equaling 1 to 7. The LSTM model performed with the most precise prediction when the number of time lags equals to 7. Once the number of time lags was greater than 7, the prediction performance became worse with a little fluctuation. The potential reason might lie on the excessive time lags made the LSTM too complex, which caused some overfitting issues with the LSTM. Thus, the prediction effectiveness was influenced by the unnecessary complexity of the LSTM.

### Evaluating the accuracy of the prediction after different days

The time interval between time-lags indicates how often a historical data point will be input into the proposed LSTM model. In this study, the frequency of road surface friction detection is once per day, then the minimum time interval between time-lags is 1-day. If the time interval between time-lags is set as 1-day, then the output would be the road surface friction after 1-day. Thus, if the road surface friction after \(l\) days is predicted, the time interval between each time-lags of the input data should be set as \(l\). By varying the time interval, the prediction time can be adjusted. Then, the model is not only dedicated for predicting the road surface friction after a fix number of days. In order to demonstrate the road surface friction prediction accuracy after different days, the proposed LSTM was trained separately by the data sets with different time interval between time-lags from 1 to 10 for all road segments. Table 3 shows the average predictive performance of the LSTM models.

Obviously, as the time interval between time lags became larger, the predictive performance of the
LSTM got worse for all three performance measurements. It suggested the accuracy of road surface friction prediction would be decreased when the predicting interval getting larger. It is noticed that, as the predicting interval became larger, the prediction accuracy did not drop too much to make the prediction accuracy unacceptable. The road surface friction prediction of 5 days later still got about 20% MAPE and relatively low MSE and MAE. Even when the time interval between time lags equals 10 days, the proposed LSTM model still got 22.39% MAPE. Figure 5 shows the boxplots of the predictive performance of the proposed LSTM models trained by the data with different days between time lags. It is explicit that, while the time interval between time-lags became large, the variance of predictive performance was getting larger for all three predictive performance measurements. The 25th percentiles of three measurements were stable as the predicting time interval getting larger. The 75th percentile increased while the predicting time interval is set from 1 day to 10 days. In summary, the proposed LSTM model is accurate for predicting short-term road surface friction. When the predicting time interval becomes larger, the prediction accuracy decreases, which is consistent with the previous research results that the road surface weather condition has short-term time-series features but long-term features (Brijs et al., 2008).

**Evaluating the influence of other related features on predicting accuracy**

The above LSTM prediction models were trained only by friction value in the past time periods. Theoretically, road surface water thickness, road surface temperature and air temperature would be the main causal factors of the road surface friction. Thus, it is meaningful to add more variables as the input of the LSTM model to explore the influence of those features to the prediction accuracy.

Figure 6 shows the scatterplot matrix of road surface water thickness, road surface friction, road surface temperature and air temperature collected by RCM 411 sensor to display the correlation among these features. The road surface temperature and air temperature has heavily strong correlation that all the dots centralized to the diagonal line. However, road surface friction seems does not have clear correlation with two temperature related measurements. The dots spread in the plots without specific patterns. In

| Time Lages | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9    | 10   |
|-----------|------|------|------|------|------|------|------|------|------|------|
| MAE (N)   | 0.0862 | 0.0836 | 0.0787 | 0.0812 | 0.0799 | 0.0800 | 0.0778 | 0.0832 | 0.0797 | 0.0824 |
| MSE       | 0.0135 | 0.0133 | 0.0117 | 0.0126 | 0.0119 | 0.0121 | 0.0112 | 0.0128 | 0.0117 | 0.0126 |
| MAPE (%)  | 17.62 | 17.82 | 16.23 | 16.97 | 16.14 | 16.57 | 15.16 | 16.81 | 15.58 | 16.65 |

**Figure 4.** Comparison of ground truth and predicted values on multiple days.

**Figure 5.** Comparison of ground truth and predicted road surface friction along E75 on 2017-10-20.

**Figure 6.** Comparison of ground truth and predicted road surface friction along E75 on 2017-12-29.

**Table 2.** Predictive performance of the LSTM with different number of time lags.
addition, the scatter plot of road surface water thickness and road surface friction presents a U-shaped pattern. The road surface water thickness reached large value when the road surface friction value is relatively large or small.

Based on the preliminary analysis of the correlation between variables, two additional experiments were conducted for investigating the influence of these features on predicting accuracy. The LSTM models were trained by adding road surface water thickness and road surface temperature. 7 time-lags and 1-day time interval between time-lags were selected for the model training. The prediction performance was compared with the prediction performance of the LSTM model trained only by road surface friction. The comparison result is shown in Table 4. As shown in Table 4, the predictive performance of the LSTM was improved by adding road surface water thickness as the additional input of the model. All three predictive performance measurements achieved lower value. It is demonstrated the statement in previous study that road weather condition is highly correlated with the rainfall in

| Time Interval (Days) | 1     | 2     | 3     | 4     | 5     | 6     | 7     | 8     | 9     | 10    |
|---------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| MAE (N)             | 0.0790| 0.0873| 0.0903| 0.0948| 0.1043| 0.1096| 0.1000| 0.1086| 0.1085| 0.1190|
| MSE                 | 0.0127| 0.0146| 0.0152| 0.0166| 0.0195| 0.0229| 0.0189| 0.0222| 0.0220| 0.0232|
| MAPE (%)            | 15.24 | 18.01 | 17.61 | 19.99 | 21.06 | 21.75 | 19.86 | 22.63 | 21.33 | 22.39 |

Figure 5. Boxplots of the predictive performance of the LSTM with different days between time lags. (a) Mean Absolute Error (MAE). (b) Mean Squared Error (MSE). (c) Mean Absolute Percentage Error (MAPE).

Figure 6. Scatter plots matrix of features.
past time period (Hambly et al., 2013). However, with the road surface water thickness and road surface temperature as the additional input of the prediction model, the predictive performance became worse than only taking road surface friction as the input in terms of all three performance measurements. By considering the weak correlation between road surface friction and temperature related measurements, the potential reason could be that the additional temperature related features made the LSTM too complicated and brought lots of useless information to the LSTM model. The weights effectiveness of useful feature could be negatively influenced by the excessively complex model structure, thus reducing the model accuracy. In previous study, the same situation was found for short-term traffic speed prediction (Cui et al., 2020a). In that study, the accuracy of traffic speed prediction of the proposed LSTM was not improved by adding traffic volume and traffic occupancy as additional features. In summary, the accuracy of the proposed LSTM prediction model was improved by combined road surface water thickness in past time period as the additional input for predicting the road surface friction after 1 day, but the accuracy was weakened by adding road surface water thickness and temperature simultaneously as the additional input due to the excessively complicated model structure.

### Conclusion and future works

This study employed LSTM NN to develop a road surface friction prediction model based on historical friction data. The road surface friction data on European route E75 from Sodankylä to Kemi collected by RCM 411 sensor was used as model input, which covered 446 days and over 186 miles in total. The road was segmented into 1,487 road segments based on the calculated road surface status. The experiments were conducted for each road segments independently, and the predictive performance of the proposed LSTM was calculated by averaging the predictive performance measurements of all road segments prediction results. For demonstrating the effectiveness of the proposed model, SVR, RF and Feed-Forward NN were selected as the baseline models for comparing the predictive performance with the proposed model. Furthermore, the impact of the number of time-lags on predictive accuracy, the influence of time interval between time steps on predictive accuracy were also tested. In addition, the experiments also analyzed the impact of adding road surface water thickness, road surface temperature and air temperature on predictive accuracy.

Based on the analysis results, the proposed LSTM road surface friction prediction model outperformed all other baseline models in terms of the lowest value of MAE, MSE and MAPE. The proposed LSTM prediction model got 0.0778 in MAE, 0.0112 in MSE and 15.16% in MAPE. The number of time-lags and the predictive time interval had influence on predictive performance of the proposed model. The LSTM prediction model achieved the most accurate prediction with 7 time-lags, and the prediction accuracy dropped when the predictive time interval was getting larger. Road surface water thickness and road surface temperature were added to the proposed prediction model as additional model input. Road surface water thickness improved the predictive accuracy, but road surface temperature did not. The findings of this study can be used to support the road maintenance plan and decision making, thus mitigating the impact of inclined inclement road surface condition on traffic safety and mobility. In the future, an improved LSTM prediction model should be developed for freeing the requirement of fixed time interval between each time-lags of one data sample. Thus, the energy and time cost for data collection can be saved, which makes the prediction model more convenient and valuable from implementation perspective.

### Disclosure statement

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