

# Near real-time monitor of railway track adhesion conditions

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## ABSTRACT

In this paper we examine the possibilities of using sensor data from trains in service to develop a real-time monitor of the adhesion conditions of the rail. In everyday railway operations, low adhesion conditions of the track are an important challenge for railway operators, since these may result in a loss of punctuality, an increase in wear of both wheel and rail, and in an increase of the risk for red signal passage in situations where trains are unable to stop in time. At the same time, prudent driving behavior while the adhesion conditions returned to normal, results in unnecessary train delays. A central issue here is that rail adhesion conditions vary across space and time. To date it is a major challenge to give accurate real-time information on adhesion conditions to train drivers and infrastructure operators. With real-time monitoring of the adhesion conditions, the drivers could adjust their (de)acceleration control to local adhesion conditions and thereby minimize wear, and the infrastructure managers could improve the track conditions by taking friction enhancing measures. In this paper we demonstrate the feasibility to detect adhesion conditions using sensor data already available in passenger trains.

To monitor the adhesion conditions of the track, we used real-time sensor data from ~20 trains. We designed an algorithm that can diagnose track sections as having either slippery or normal adhesion conditions. Specifically, we trained a logistic classifier on a data set that contained reported rail adhesion conditions as well as sensor data from trains in service, such as information about traction, velocity, excessive wheel slip/sliding detection, and weight. We then assessed the performance of this classifier using an independent test data set.

This first assessment shows a classification accuracy of approximately 77%, with a ~23% false positive rate and a ~23% false negative rate, when compared to the drivers reporting. Several improvements are proposed to increase the sensitivity, which outline the directions of our future research towards the implementation of a real-time monitor of railway track

adhesion conditions.

## 1. INTRODUCTION

Every railway operator, infrastructure manager and even the passengers know the problem: autumn comes, leaves fall and the railway tracks get slippery. Extended traveling times and disruption of the schedule are often the result. Low adhesion conditions on the track can have several causes. Apart from leaves in combination with moisture, also other substances can cause a decrease of adhesion. Examples of this are the combination of rust and moisture, precipitated air pollution, e.g from chemical plants, friction decreasing lubricants that are sometimes applied in curves, or the output of the trains toilet when it is deposited on the track (Van Steenis, 2010).

The consequences of low adhesion reach beyond disruption of the schedule. Wheel slip and sliding causes damage to the rolling stock and the track. Extreme low adhesion may also have consequences for safety (Van Steenis, 2010).

Currently NS, which is the principal railway operator in the Netherlands, has two systems in place to alert the drivers and the traffic controllers of low adhesion conditions. The first measure is a low adhesion prediction model from the infrastructure owner ProRail that is mainly based on the weather conditions. This model identifies regions and time intervals where the probability of slippery tracks is increased. The second system to alert drivers and traffic controllers comes from the drivers themselves. When they notice slippery tracks they report this to the traffic controllers who in turn will warn the drivers passing that region in the next two hours. Moreover they take other measures to secure safety if needed.

These systems are, however, not perfect. The prediction model is modestly accurate, and also the driver's observations are neither complete nor always true. Moreover, the duration of the low adhesion conditions is unknown and is currently heuristically estimated to two hours from the moment noticed. However, it can be longer or shorter. If the low adhesive track is back to normal within two hours, unnecessary prudent driving results in unnecessary train delays. On the other hand, if the adhesion is still low after two hours, unnecessary dam-

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ages to wheel and rail could occur. Hence it would be of great value to have a real-time, accurate and objective measure of the adhesion conditions of the track. Drivers and traffic controllers could be warned more accurately, hence safety measures and adjusted driving behavior can be deployed if and only if needed. An additional advantage is that an objective measure of the adhesion conditions can help to improve the prediction model, which in turn is particularly useful when applying preventive measures against low adhesion.

In an ideal world train drivers, traffic controllers and infrastructure managers would have near real-time information about the level of adhesion that is time and space dependent and covers the entire track. Many existing field measuring systems are custom built vehicles especially designed to determine the friction of the track (Magel, 2017). With a small amount of such vehicles it is impossible to give accurate near real-time information at all locations. When only low cost sensors would be needed, many trains could be equipped with them and many vehicles could contribute to the measurement. Hence near real-time data would be available for all locations. Hubbard et al. pursue methods using information from such low cost sensors that could be mounted on many trains in normal service. The methods are based on the dynamics of the system (Hubbard, Ward, Goodall, & Dixon, 2012; Hubbard, Amarantidis, & Ward, 2016), and until now tested on simulated data.

We propose an approach with different sensors that are already available on the trains of NS. To the best of our knowledge the novelty of our work lies in demonstrating the usage of real-world data collected by passenger trains, to detect adhesion conditions. Recently the NS started a project to send the information from the train sensors to a central server in real-time fashion. At the moment we have real-time access to data of approximately 20 trains for analytics and health monitoring. The main purpose of this research is to investigate whether it would be feasible to use available sensor data from the train to monitor the adhesion conditions of the track, while the train runs in normal service. Consequently, we do not aim at building a full model in this first assessment. Such model would benefit the train operators and traffic controllers, but also the maintainers of the track.

We start in Sec. 2 with outlining the method, followed by the results in Sec. 3. We continue with a discussion in Sec. 4 and finalize with a conclusion and plans for future work in Sec. 5 and 6.

## 2. METHOD

To investigate the possibilities to detect low adhesion from trains in service with the available sensor information, we run multiple logistic regression (Cox, 1958) with derived quantities of the train sensor information as predictors and the drivers reports as labels.

### 2.1. Available data

We use sensor data from trains that were collected and sent wireless to the shore (a data center) in real-time. This data is stored in a database for off-line processing—which we used for the analyses presented in the current work—but is also available for real-time analysis. We focus on the following data that is available for a subset of all trains in the NS fleet: the location of the train, the requested and applied torque, the load of the train, the detection of wheel slip and the velocity of the train. Wheel slip detection occurs when the percentage of slip, derived from the difference in angular velocity between the different wheels of the coach, exceeds a certain threshold. The load of the train is estimated from the value of the sensor that is used to regulate the amount of air in the air springs between the bogie and the coach. This data is time-stamped and sent in real-time to the shore. Evidently the location and time of the train are important, since this allows taking into account the spatio-temporal dependence of adhesion conditions. The combination of the applied torque and the load of the train can give insight in the level of adhesion, since the coefficient of adhesion is defined as:

$$\mu_{\text{adhesion}} = \frac{F_T}{F_N}, \quad (1)$$

where  $F_T$  is the tangential force that is transferred from the wheel to the rail and  $F_N$  is the normal force. The adhesion coefficient is limited by the friction coefficient of the track. The combination of applied torque and the detection of wheel slip can give insight in the amount of force that can be transferred from the wheel to the rail without wheel slip. In addition, the amount and variability in torque requested by the train driver could indirectly be a predictor for adhesion conditions, since it reflects the drivers behavior, in particular their prudence. At NS this information is available, in real-time, from about 20 trains during passenger transport service. All information is updated with a frequency of 1/3 Hz, except for location, which is available with a frequency of 1/10 Hz.

In order to assess the feasibility of a near real-time monitor of the track adhesion from available sensor data, we limit the spatial accuracy to the level of a track section. In this paper we define a track section as the area around a station, or the piece of track between two consecutive stations. We only consider the former, i.e. sections around a train station, and limit ourselves to cases where a train arrives at and departs from a train station. A train passage refers to a train passing a track section at a specific time. We look at the time interval from 3 minutes before arrival till 3 minutes after departure.

We aggregate the above mentioned data on train passage level in several different ways. An important quantity to detect low adhesion conditions is the amount of slip detection per passage. We look at the total amount of slip in the  $X$  seconds after departure, since then the acceleration and hence the prob-

Aggregated quantity	Explanation
sum slip over adhesion	$\sum_{t \in P} \sum_{i=1,2} \frac{S_i(t)m_i(t)}{\tau_i(t)}$
total slip during passage	$\sum_{t \in P} \frac{\sum_{i=1,2} S_i(t)}{N_P}$
slip in $X$ seconds after departure	$\sum_{t_d \leq t \leq t_d + X} \frac{\sum_{i=1,2} S_i(t)}{X}$
max actual torque	$\max_{t \in P} (\max_{i=1,2} \tau_i^{ac}(t))  _{S_{1,2}(t)=0}$
max requested torque	$\max_{t \in P} (\max_{i=1,2} \tau_i^{rq}(t))  _{S_{1,2}(t)=0}$
max adhesion	$\max_{t \in P} \left( \max_{i=1,2} \frac{\tau_i(t)}{m_i(t)} \right)  _{S_{1,2}(t)=0}$

Table 1. Aggregated variables. Here  $t$  denotes the time in passage  $P$  with  $N_P$  measurement points and  $t_d$  denotes the time of departure,  $i$  runs over the two coaches that have a traction installation,  $S \in 0, 1$  denotes wheel slip detection if equal to 1,  $\tau$  denotes the requested (rq) or actual (ac) torque and  $m$  is proportional to the mass.

ability for slip is the biggest. We also take into account the total amount of slip. Since prudent driving behavior of the drivers can avoid slip detection events, even under slippery conditions, we also look at quantities such as the maximum of the reached adhesion under the condition that no slip detection occurred, or the maximum of the requested torque. The maximal actual torque under the condition that no slip occurs can help in detecting that it is not slippery. We also look at the sum of the ratio between the slip and adhesion, which is a quantity inspired by the work of van Steenis (Van Steenis, 2010). For a precise specification of the quantities, see Tab. 1. The result of this aggregation is a table containing for each train passage: the time of the passage, the train number and several aggregated quantities based on slip detection, requested and actual torque and a quantity correlated with the load.

To each train passage we attach a slipperiness-label on the adhesion condition. These labels originate from the driver's observations reported through the current train-shore communication system of alerting for low adhesion conditions as was outlined in Sec. 1. Note that these labels do not reflect the 'perfect' truth about adhesion conditions for two reasons. First, drivers do not always notify the traffic controller of slipperiness, hence the lack of driver observations does not necessarily mean that it is not slippery. The second reason is the duration of the slipperiness. After a driver communicates that a track section is slippery, this label remains associated with that track section for the next 2 hours although adhesion conditions may return back to normal in less than two hours. In order to improve the reliability of passages labeled as *not slippery* we restricted the not-slippery passages to completely dry days in July 2017 between 10 a.m. and 4 p.m. In order to

improve the reliability of the *slippery*-label, we removed passages where the driver used maximal traction ( $\tau > 6000$  Nm) for at least 4 measurements without experiencing any wheel slip. Finally we clean our data by removing passages with insufficient measurements (due to not sufficient data transferred from train to shore) and where the train never reaches a speed of at least 50 km/h. The latter is removed, because low maximal speed often means a low acceleration and hence not much information to detect low adhesion conditions.

## 2.2. Logistic regression

We limited our research to data from July and October 2017, which resulted with the above outlined procedure in approximately 1000 passages of which approximately 25% was labeled as slippery. To avoid circularity, we divided the passages into a training and test set so that days with an even day number were used for training and days with an odd day number were used for testing. As a general approach, we train a logistic regression model (Cox, 1958) as implemented in scikit-learn (Pedregosa et al., 2011) with one or more variables in the training set and assess the model with the test set by comparing its predictions to the slipperiness-labels. In all cases we construct the Receiver-Operator Characteristic (ROC) curve and quantify each model's performance using the Area Under the Curve (AUC).

In Sec. 3.1, we assess to what extent slip detection alone can predict slipperiness. We use a single variable logistic regression using the frequency of slip for time intervals of 5, 10, 20, 30 or 30 seconds after departure as well as for the full duration of the passage. Frequency of slip was computed by dividing the number of detected wheel slip events by the duration of the time interval.

In Sec. 3.2 we assess the effect of other variables (see Table 1), as well as the combination of multiple variables in a single model. Specifically, we start with comparing AUCs using a single variable. Then we consider all possible combinations of two variables and see which combination yields the highest AUC. We then extend this to all combinations of three variables. To find which model is at the same time most predictive and most simple, we continue this process until we do not observe an increase of maximum AUC (over all combinations of variables) by adding another predictor variable to the model.

In Sec. 3.3 we consider using predictions from the previous train on the same location. The rationale is that adhesion conditions usually change slowly over time, so that a prediction for a certain passage could potentially be enhanced by considering a prediction from the previous train at the same location. To do so, we trained and tested two logistic models that are both trained on the same training set. The first model is trained on the quantities of one train passage. Next, the training set is augmented with the prediction of the first model that

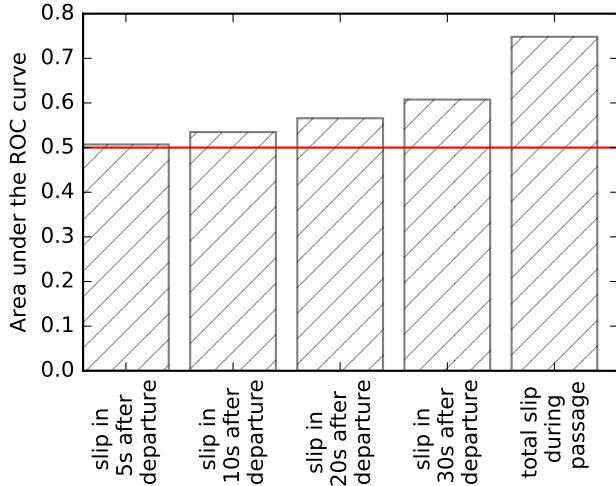


Figure 1. Area under the ROC curve (AUC) for different ways of aggregating the amount of slip per passage.

belongs to the previous train on the same location. The second model is then trained on the quantities of one train passage plus the prediction of the previous train passage from the first model. Both models are then used successively on the test set: first the test set is augmented with the prediction of the previous train on the same location as predicted by the first model, and then the second model is used to make a prediction that considers also the prediction from the previous passage. Note that no circularity occurs because, by construction, predictions for the testing data are not at any point based on the slipperiness-labels in the testing data. Cases when no train was found for a certain passage in the previous two hours were excluded as training or testing data.

Our data is unbalanced, with less passages reported slippery. We also ran our models using balanced data, where a subset of the non-slippery passages were removed. This resulted in very similar outcomes, which we do not report in detail here.

### 3. RESULTS

#### 3.1. Single variable: slip detection

We used logistic regression (Pedregosa et al., 2011) to investigate the predictive value (as quantified by AUC) of slipperiness aggregated over temporal intervals of different duration. As illustrated in Figure 1, the total amount of slip detection during the entire passage has more predictive value than the amount of slip detection during intervals of 5, 10, 20 or 30 seconds after departure. A monotonic increase of the AUC is observed when the time span increases from 5 to 30 seconds and to the entire passage. Note that considering only the amount of slip will not be sufficient for a proper detection, since (extreme) careful driving behavior can result in no slip detection at all even though the adhesion conditions are

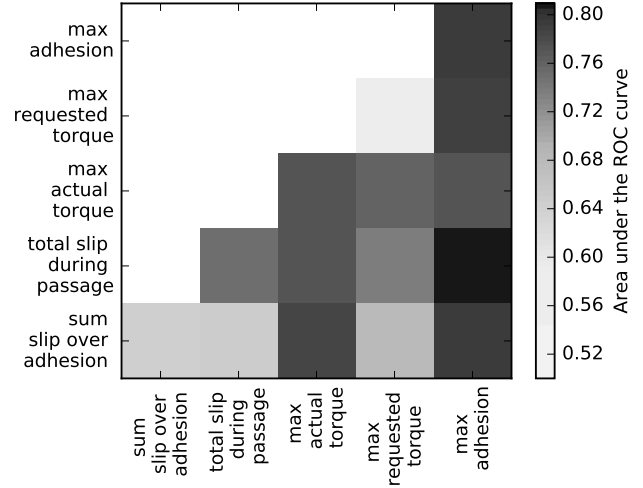


Figure 2. Area under the ROC curve (AUC) for different combinations of variables in two variable logistic regression model.

low. Therefore, in the next section, we also consider the effect of other variables. Because slip detection over the full passage was more predictive than using shorter intervals and of course the different ways of aggregation are strongly correlated, in the next subsection we do not consider variables based on these shorter intervals.

#### 3.2. Increasing the number of predictive variables

To explore which variable or pairs of variables has most predictive power, we run a two variable logistic regression for all single variable and all pairs of two variables (see Table 1). Figure 2 shows the AUC for the different two variable models, where elements on the diagonal represent AUC for single variable models. By inspecting the diagonal we can already conclude that the following three aggregated quantities are most informative for slipperiness prediction: *total slip during passage*, *max adhesion*, and *max actual torque*. The combination of the first two aggregated quantities turns out to be the best combination of two variables as can be seen from the off-diagonal elements in fig. 2.

We also try all combinations of three variables, as well as all variables together. However, neither of those models performs better than the model based the best two variables. For simplicity (Ockham's razor), in the next subsection we only use those two variables to assess the effect of predictions from a previous train on the same location.

#### 3.3. Previous adjacent location

In (Van Steenis, 2010) it was observed that when low adhesion occurs, it usually affects consecutive trains within the next two hours. Therefore we expect that our model would improve by taking into account a prediction of a recent pre-

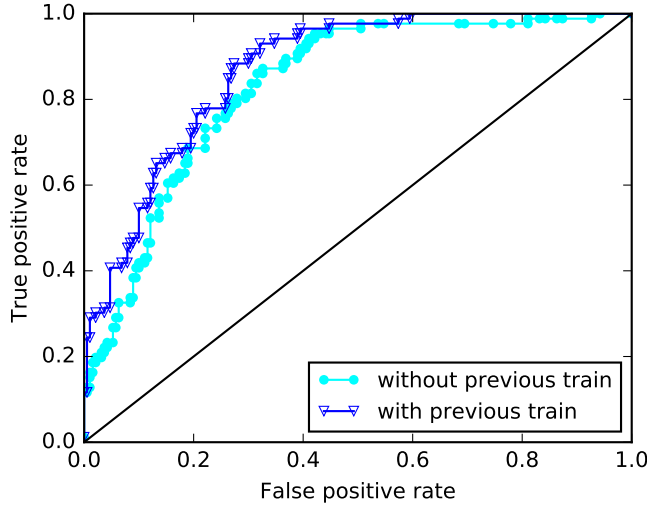


Figure 3. ROC curves without (cyan filled circles) and with (blue open triangles) taking into account the previous train on the same location into the logistic regression model.

		Algorithm:	
		slippery	normal
Driver:	slippery	77.9%	22.1%
	normal	22.6%	77.4%

Table 2. Confusion matrix of the best model including the previous train prediction evaluated at the threshold of 0.132 that gave a good balance between the false positive and the false negative rates.

vious train passage at the same location (track segment). We apply a sequence of two models as described in Sec. 2.2. We compare the performance of the first model alone to the sequence of the first and the second model. In both cases the input quantities are the total amount of slip and the maximal adhesion. For the second model this is augmented with the prediction of the previous train. As shown in Figure 3 the ROC curves are shown for both these approaches. The combined model that includes the prediction of the previous train (blue open triangles) performs better than the model that bases its prediction on a single train (cyan filled circles).

The model with the best predictive value is based on the total slip per passage, the maximal adhesion and the prediction of the previous train on the same location. The model gives a probability for the passage to be slippery. The threshold should be set to separate the continuous prediction of the model in slippery and normal. When taking the threshold that balances the false positive rate and the false negative rate best, we find that approximately 77% of the passages are correctly detected, with a false positive rate and a false negative rate of about 23%, see Tab. 2.

#### 4. DISCUSSION

The results look promising, but some false positives and false negatives are still present. Regarding the false negatives we have to mention that it is possible that the track was in fact not slippery, given the procedure of labeling as was mentioned in the end of Sec. 2.1. Following the current procedures at the NS, the driver's notification of low adhesion conditions stays in place for a heuristic time period of two hours. However it is possible that the adhesion conditions have improved earlier. When we look closely at the speed and traction profile during these passages, we see in about half of the cases no sign of slipperiness. However, we often see that the driver still adjusts his behavior and accelerates slower than normally. In these cases it is hard to determine whether the adhesion conditions went back to normal, or that the driver is exactly careful enough not to cause any wheel slip.

A closer look at the false positives reveals that many of those wrongly diagnosed passages show similar characteristics. In almost all cases the driver departs slowly by requesting only a limited amount of torque, which might be due to signals along the track. Although there is no wheel slip during the passage, the maximal adhesion during the passage is quite small, since it is bounded by the requested torque.

It is most difficult to predict passages where the train does not accelerate to full or nearly full speed due to signals or speed limits. The reason is that reduced speed in many cases implies less acceleration and hence less probability for wheel slip. In these cases it is interesting to take into account the predictions of the surrounding areas in a similar manner as we take into account the prediction of the previous train, or to take the signals themselves into account. These areas could give more information, since they could be characterized by a higher acceleration. In this way one takes into account the spatial smoothness of low adhesion conditions.

To the best of our knowledge few research has been reported on methods to detect the rail way track adhesion conditions for all locations nearly real-time. However, an interesting approach can be found in (Hubbard et al., 2012, 2016), where the authors develop two methods to detect low adhesion from trains in normal service. Both methods use the change of the vehicle dynamics as a function of the adhesion conditions. One method estimates creep forces based on a linear model and the Kalman-Bucy filter (Hubbard et al., 2012). The other method assesses the relationship between the dynamical responses under different adhesion conditions (Hubbard et al., 2012). The methods look promising and are explored further (Hubbard et al., 2016), although the related RSSB project has ended (RSSB, 2014). To our best knowledge these methods are tested on simulated data only, which makes a direct comparison to our work difficult. However, both our method and the methods based on the vehicle dynamics (Hubbard et al., 2012, 2016) have the advantage that all trains could

contribute to the measurement, since the sensors are either already available, or quite cheap. This allows for monitoring adhesion conditions nearly real-time with detailed spatial coverage. Both approaches have in common that they aim at detecting low adhesion rather than precisely measuring the adhesion or creep curves, which is the aim of most specially designed measurement vehicles (Magel, 2017).

## 5. OUTLOOK

Looking at the speed and traction profile of the false negatives, we saw that some passages indeed did not show any hint of slipperiness. The driver could depart with maximal acceleration without slip detections. Also the speed and traction profiles of the false positive sometimes clearly showed that it was slippery indeed. Therefore we plan to improve our model by implementing some physical rules. The following observations could for example imply slipperiness:

- More than  $N_{\min}$  wheel slip detection events
- Wheel slip detection for traction values smaller than  $\tau_{\min}$

On the other hand, one could think of observations that imply that the adhesion conditions are fine, for example:

- The traction is for more than  $t_{\min}$  time above  $\tau_{\text{ref}}$  without wheel slip.
- Braking with more than  $\tau_{\text{ref}}^{\text{br}}$  torque is possible without wheel slip

Apart from improving our model, we also think that physical rules make it easier for the drivers and traffic controllers to accept the detection of the model. An other improvement could be to include data from other train types, in particular from commuter trains that stop very often. The NS is currently in the process of incorporating other train types into the real-time monitoring project, which enables us to use the data from the data center. Other data sources could also improve the model, for example the prediction of slippery areas from the prediction model used by ProRail, or weather conditions like humidity, clouds, frost, etc.

In this paper, we tested our model against drivers notifications, which are known to be neither complete nor always true, although they are a good first estimate. In the future we plan to test the model further with a selected group of drivers that will be asked to pay special attention to slipperiness and to always report to the traffic controller. In the best case scenario we could ask them for feedback when our model and their observations do not agree. In this way we improve the quality of the labels.

## 6. CONCLUSION

In conclusion we show the feasibility to detect low adhesion from the traction and wheel slip detection sensors in the train to warn drivers for slippery conditions. The sensor data is

available for most modern trains, which limits the costs for implementation. Important information is the amount of slip that occurred and the maximal adhesion that is used. The more trains pass a specific track section, the more information is available and the more accurate is the detection system. Importantly, the sensors are already available in passenger trains so the model can be developed and tested with real-world data. However, it is important to note that, as long as the model has false negatives, it can only be used for warning the drivers for low adhesion. It is not yet strong enough to ensure proper adhesion conditions, since a false negative could result in a safety risk. However, the model can be valuable to pin-point the locations where the infrastructure manager can apply friction enhancing measures.

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