Texture Depth Prediction Using Distress Deterioration Curves

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Abstract

Road Surface Texture Depth (STD) is a critical aspect of a road surface. A typical STD range is between 2.0-0.8 mm. Roads with STD less than the lower threshold are more prone to traffic accidents due to aquaplaning or drop in skid resistance. Roads with STD more than the upper threshold are prone to fretting and pothole formation. In this study, a simple method to predict STD has been developed. The method utilises previous STD measurements collected by the Surface Condition Assessment for the National Network of Roads (SCANNER) method to quantify STD deterioration rate, which is the amount of increase or decrease in STD over time. The deterioration rates are then converted into Texture Deterioration Master Curves (TDMCs) which can be used in predicting STD. To demonstrate the application of this method, SCANNER data covering around 400 km of class A roads in Nottinghamshire collected between 2014 and 2018 were analysed and used to build TDMCs. STD data in 2020 were then predicted and compared to the measured STD data for validation. The results show that the developed method is simple and reliable, which makes it a valuable management tool for highway authorities enabling them predicting the STD on their road networks and assessing the risks of high or low STD on the condition and operation of their road networks.

1- Introduction

Road Surface Texture Depth (STD) can be defined as a measure of deviations in height and depth on the road's surface from a smooth road surface profile. The deviations can vary from as small as a few micrometres, which is mostly related to particle surface roughness, to tens or hundreds of millimetres, which is mostly related to the used aggregate gradation and asphalt mix volumetrics, or road unevenness. Therefore, researchers have classified road texture based on its amplitude (A) and wavelength (λ), which is the distance between two texture amplitudes into four categories: microtexture ($A \leq 0.2$ mm and $\lambda \leq 0.5$ mm), macrotexture ($0.1 < A \leq 20$ mm and $0.5 < \lambda \leq 50$ mm), megatexture ($0.1 < A \leq 50$ mm and $50 < \lambda \leq 500$ mm), and Unevenness ($\lambda \geq 500$ mm) (Chen et al., 2022; Wambold et al., 1995). Every one of these categories have significant effects on the interaction between the road surface and vehicle tyres, and affect the safety of road users and sustainability of roads during the use phase.

At micro and macro surface texture levels, STD impacts on road safety and traffic accidents can be analysed by its effects on critical road surface aspects, which are skid resistance and vehicle hydroplaning. The relationship between STD and skid resistance has been under investigation since the Fifties of the previous century (Sabey, 1966); the main conclusion of this study is that skid resistance on wet roads depends largely on the "coarseness" of the road surface, which will not drop significantly if the road has a textured surface. It also recommends limiting the STD on roads to more than 0.6 mm to ensure acceptable level of skid resistance. On the other hand, the combination of a good STD and worn vehicle tyres has been found to significantly decrease the risk of "vehicle hydroplaning", which is the inability of vehicles to brake and steer on wet roads (Horne & Joyner, 1966). This is because the STD provides drainage channels for water at the road surface to escape, which ensures a good grip between the road surface and vehicle tyres.

The relationship between STD and traffic accidents has been thoroughly investigated by many researchers and highway organisations. A Transport Research Laboratory (TRL) study (Roe et al., 1991) has shown that maintaining the macrotexture above 0.7 mm reduces the risk of accidents in wet and dry conditions as well. Another TRL study that investigated the relationship between collisions and skid resistance and included various modern road surfacing materials (Wallbank et al., 2016) concluded that STD prevents vehicles from skidding on wet roads and also increases surface friction in all weather conditions, which means maintaining sufficient STD reducing the risks having traffic accidents in wet and dry conditions. Several other studies have also demonstrated that smooth road surfaces increase the risks of vehicle accidents and the STD must be kept in certain limits to ensure good vehicle tyre grip, high skid resistance, and low risk of hydroplaning (Fairall et al., 2021; Fernandes & Neves, 2014; Pardillo Mayora & Jurado Pina, 2009; Spitzhuttl et al., 2020).

In addition to the critical effects of STD on road safety, it has critical impacts on other aspects. Tyre-pavement interaction noise has been one of the main concerns due to noise effects on the ecological environment and surrounding population. Various studies have shown that vehicle noise is a function of STD and other factors such as air void content at the surface, vehicle type, speed, and tyre tread pattern (Descornet et al., 2000; Franklin et al., 1979). Sandberg (1999) demonstrates that the relationship between STD and noise is complex and STD can decrease or increase noise depending on texture wavelength, vehicle type, vehicle tyre texture and vehicle speed. With respect to fuel economy, this is a critical topic that has been extensively investigated due to the critical effects of fuel consumption on the environmental, economic, and social impacts of roads during the use phase. The effect of STD on vehicle fuel consumption can be understood by the direct relationship between rolling resistance and fuel consumption (Thom, 2008). STD of more than about 5mm increases rolling resistance and eventually fuel consumption, and driving on very rough roads can increase fuel consumption by 11% in comparison with driving on very smooth roads (Bendtsen, 2004). Several other studies have also demonstrated similar conclusions (Chatti & Zaabar, 2012; Ejsmont et al., 2016; Levesque et al., 2023; Perrotta et al., 2017).

Due to the aforementioned paramount effects of STD, highway authorities and researchers have developed different methods to measure and quantify the surface texture of roads. The sand patch (BSI, 1990; Cooper, 1974) is one of the earliest methods to quantify the Mean Texture Depth (MTD) of a pavement surface. This method has been extensively used to estimate skid resistance on roads. It is however a slow method that gives a single texture measurement every reading, and it is also an unpractical method as it requires traffic stoppage when used for texture measurement on roads. Therefore, different automated traffic speed texture measurement methods have been developed over time. The Transport Research Laboratory developed a high speed texture meter using a contactless laser reflectance sensor (Roe et al., 1988) which is able to measure texture depth and produces a texture profile at traffic speeds between 10 and 100 km/h. This method of texture measurement has been used to monitor texture depth during the use phase of roads and to investigate texture related traffic accidents (Roe et al., 1991). The capability of texture measurement by laser sensors has evolved to include 3D texture scanning (Chen et al., 2021), which enables analysis of texture distribution and roughness characterisation. Moreover, with the advancement in imaging technologies, various studies have proposed image-based texture depth measurements, which allows for analysing the entire texture distribution over a pavement surface (Chen, 2018; Matlack et al., 2021; Wang et al., 2022).

It can be seen that a lot of significant work has been done to measure and monitor STD to ensure it remains within accepted criteria. Very little work, however, has been done on predicting STD over time. In this study, a STD prediction tool has been developed. The tool is basically a statistical model that has been developed based on previous texture depth data quantified by the SACNNER method. The tool requires the last two texture depth readings to predict the future. In particular, two readings are required to establish the tendency of the section, whether it has a decreasing or increasing texture depth. The last reading will then be used to predict STD based on the specified prediction period and the relevant model. The validation results of this tool show it is very reliable and easy to implement. Moreover, since this tool has been developed based on the data collected by the Surface Condition Assessment for the National Network of Roads (SCANNER) method, which is the method used by local authorities in the UK to inspect their road networks (UK Roads Board, 2011), then the local authorities in the UK can confidently implement it. Furthermore, since other data such as road geometry are also available from the SCANNER machine, then complementing these data with traffic data and use of available models such as accident prediction or pothole prediction models make this tool a strategic management tool, where the predicted condition of the network can be used to predict the consequences of STD in a scenario analysis approach.

2- Materials and Methods

2-1 Data description and pre-processing

The surface texture measurement data used in this study has been taken using the SCANNER method, which uses laser sensors to quantify the texture. The data covers around 400 km of class A roads in Nottinghamshire, as shown in Figure 1; every point on this figure represents a texture measurement expressed as an average over every 10 m of the inner lane of the road sections. The road sections had been surveyed between 2014 and 2020 every two years. These data however may contain inherent issues such as error in measurements, inaccurate section boundaries, or missing data. Therefore, the data must be pre-processed to ensure only reliable data is used in the model building. Several statistical methods are available to pre-process in these situations, such as outlier removal in the case of measurement error, averaging in the case of missing data, or combining sections and averaging in the case of inaccurate section boundaries (Kargah-Ostadi et al., 2019). In this study, the outlier removal method has been used to remove sections with a significant increase or decrease in STD over any two years. The removal rule regarding the increasing STD case is that any section that exhibits an increase of more than three times the initial reading in two years was removed; this is because this section was most likely suffering from localised damage, poorly constructed, or there was an error in the measurement. The removal rule regarding the decreasing STD case is that any section that exhibits a decrease in the texture of more than 75% of its last reading in two years was removed, this is because that section could be located at a location subjected to critical surface friction, which makes it deteriorating at a rate significantly different from the average, or there was an error in the measurement. Both of these rules have been developed in this study based on significant data analysis and observation of the texture deterioration tendency over time.

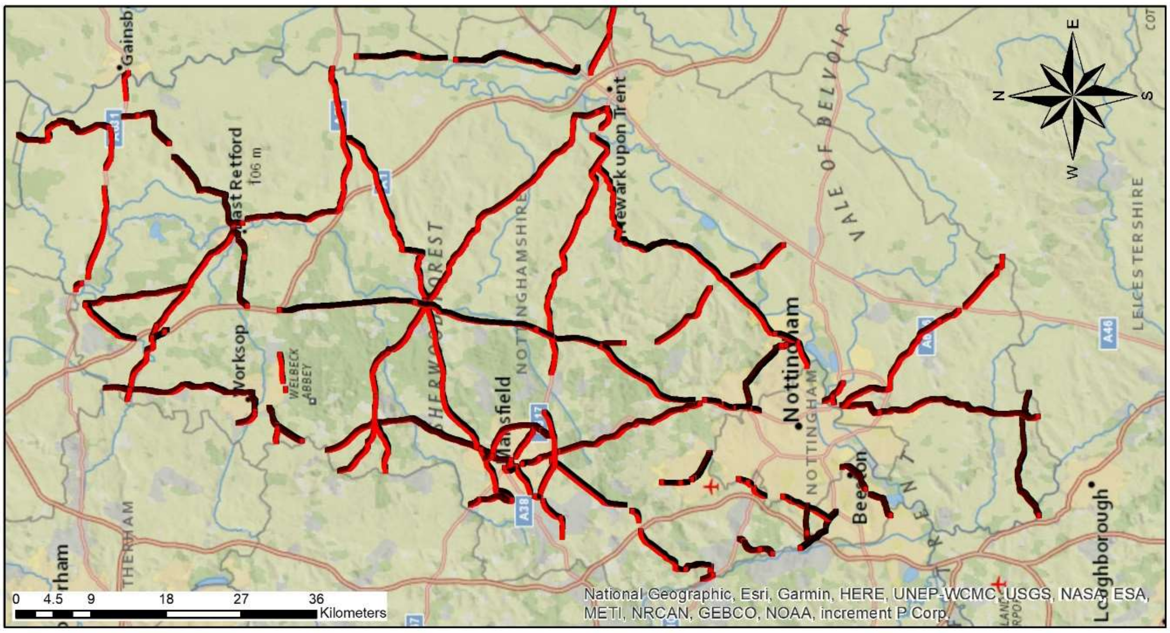

Figure 1. A map showing the study area and the road sections used in this study (every point represents a 10 m length road section; bridges, roundabouts, and intersections were not included in the scan)

2-2 Model development

Road surface texture either decreases over time mainly due to polishing by vehicle tyres, or increases over time due to fretting or ravelling of the surface. Both conditions can be represented as a rate of deterioration, which can be represented using the following form:

$$TDDR_i = (STD_i - STD_{i-1})/((T_i - T_{i-1}) \quad \text{Equation 1}$$

where *TDDR* is the texture depth deterioration rate in mm/year, *STD* is the texture measurement, *T* is the time of the survey in years, and *i* is the survey number. Previous studies, however, have demonstrated that pavement deterioration is in general a function of its condition in addition to the environment and traffic loadings (Abaza, 2014; Abed et al., 2023b). Therefore, to include the effects of pavement condition on *TDDR*, the previous equation can be rewritten as follows:

$$TDDR_{i,s} = (STD_{i,s} - STD_{i-1,s})/((T_i - T_{i-1,s}) \quad \text{Equation 2}$$

where s refers to texture depth state represented by its magnitude. This means that the deterioration rate of texture is related to its current state represented by the texture magnitude.

Following this understanding, the data collected 2014 and 2018 has been filtered as explained in the previous section. Then the sections that showed decreasing texture over time have been isolated and used to calculate the TDDR of the decreasing texture case; the rate of these sections is referred to as $TDDR_d$. Since the TDDR is related to the texture state as mentioned earlier, then the deterioration rate has been calculated cross different initial texture states as shown in Figure 2. This figure has been produced by considering five initial texture depth states, which are 0-0.5, 0.5-1, 1-1.5, 1.5-2, and 2-2.5 mm. The data show that it is very unusual to find an initial texture depth state of more than 2.5 mm regardless of the asphalt mix used. Then the sections in every state in 2014 were isolated and monitored till 2018. Lastly, the average texture depth of these sections was plotted against time and a linear model was fitted as shown in the figure. The slope of the fitted lines represents the average $TDDR_d$ of every texture state. Despite this figure showing that the relationship between texture depth and time is approximately linear, the $TDDR_d$ actually increases with the increase in the initial texture depth magnitude, which means the overall relationship is not quite linear.

Similarly, the sections that showed increasing texture over time have been used to calculate the average texture increase rate, which is referred to as $TDDR_i$, as shown in Figure 3. This figure demonstrates that the increase in the texture is related to the initial texture state; the larger the initial texture the larger the increase rate. The increase in texture depth over time is mostly likely related to pavement surface fretting, which is defined as the loss of bitumen or fine aggregate particles from a road surface, ravelling, which is the disintegration of coarse aggregate particles from the road surface (Abouelsaad & White, 2021; Scott et al., 2008), or stripping which is the displacement of bitumen on the aggregate particle surface by actions of water (Bagampadde et al., 2011). The results in Figure 3 suggest that texture can increase at any state or stage in a pavement service life. This could be on newly constructed roads with initial texture depth between 1-2 mm, or sections that suffered from ageing, moisture damage, and traffic action after some time in service, with texture depth below 1 mm, or sections with existing fretting or ravelling which most likely are those ones texture depth more than 2 mm.

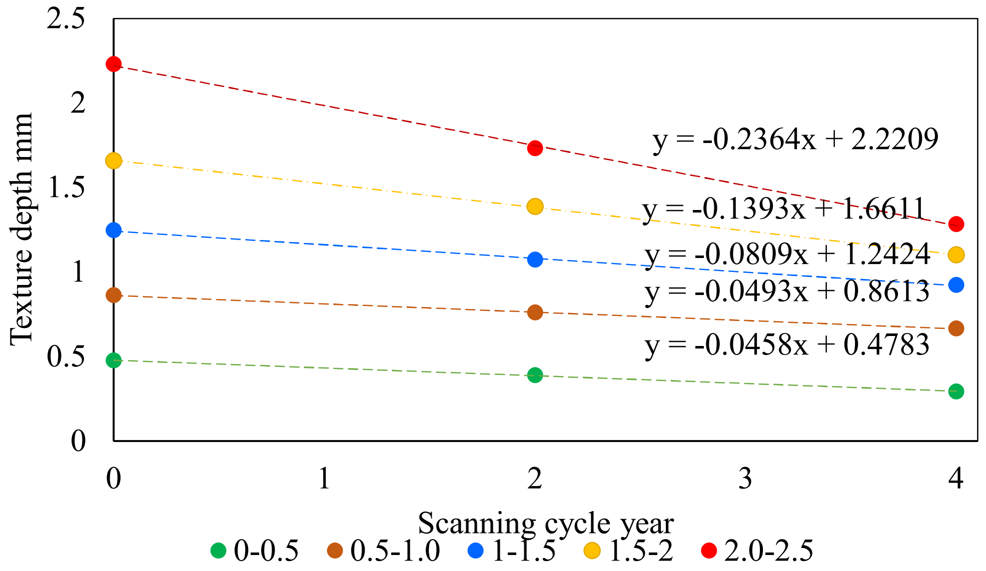

Figure 2. Average $TDDR_d$ calculated based on 2014 and 2018; the negative slope sign means the texture is decreasing over time.

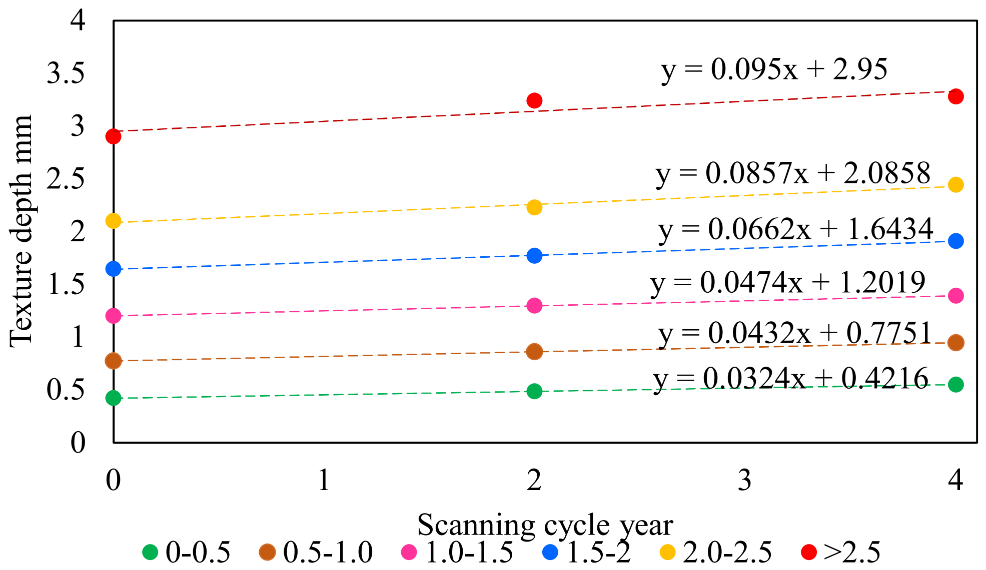

Figure 3. Average $TDDR_i$ calculated based on 2014 and 2018.

The fitted linear models in Figure 2 and Figure 3 can be used straight away by simply using the initial texture depth state to select the relevant model. This however will make the number of models to be used in the prediction process relatively large. Therefore, another approach has been followed in this study, converting the fitted linear models onto one master curve called Texture Deterioration Master Curve (TDMC). This can be done by following the procedure proposed by (Abed et al., 2023b); basically, the texture depth data are moved to the right on the x axis without changing the y axis until the data form a smooth shape, as shown in Figure 4. The rationale behind this approach is that the deterioration rate, which is the slope of the fitted lines, matches the slope of the fitted master curve to the shifted data. This can be achieved by keeping the y axis and the time spacing between the shifted data (i.e., two years in this case) the same, which means the deterioration rate is the same but calculated at a different time. It must be stated here that the shifted time on the x axis is an imaginary time that has a mathematical importance when calculating the deterioration rate but no physical meaning. In other words, it is not related to the age of the roads. The resulting shape can then be modelled using a suitable model. In this study, exponential models have been found to best fit texture deterioration data, as shown in Figure 5 and Figure 6. These figures suggest that the fitted models are very accurate with a coefficient of regressions (R^2) of more than 0.98 in both cases.

To use the developed TDMCs, two inputs are required: firstly, the last two texture depth measurements to establish whether the texture is increasing or decreasing on that particular section; secondly the last reading to predict the texture in the future. An example of this process is shown in Figure 5. In this example the last texture depth measurement is projected onto the TDMC to identify the imaginary time, then the prediction period (PP) is added to the imaginary time; the next step is to project the new time on the master curve; and lastly to project the result of the last step on the y axis to predict the texture in the future. Mathematically, this model can be derived as follows:

1. In the case of decreasing texture depth, the model fitted to the resulting master curve is as follows:

$$STD_i = 2.0355 \times e^{(-0.095 \times T_i)} \qquad \text{Equation 3}$$

2. To calculate the imaginary time of a texture depth Ti, the above model can be inverted, as follows:

$$T_i = 10.526 \times ln(2.035/STD_i) \qquad \text{Equation 4}$$

3. To add the prediction period to the model, then we can use the following form:

$$T_{i+1} = T_i + PP = 10.526 \times ln(2.035/STD) + PP \qquad \text{Equation 5}$$

4. To predict the texture in the future, the following model should be used:

$$STD_{i+1} = 2.0355 \times e^{-0.095 \times T_{i+1})} \qquad \text{Equation 6}$$

5. Since T_{i+1} is calculated in step 3, then it can be substituted in step 4, as follows:

$$STD_{i+1} = 2.0355 \times e^{-0.095 \times (10.526 \times ln(2.035/STD) + PP)} \qquad \text{Equation 7}$$

6. Lastly, the above equation can be simplified, which yields the following model:

$$STD_{i+1} = STD_i / e^{0.095 \times PP} \qquad \text{Equation 8}$$

The model shown in Equation 8 can be used to predict STD after a prediction period (PP) substituted in years using the last STD measurement.

Following the above steps, the prediction model of the increasing STD case can also be derived, which yields the following model:

$$STD_{i+1} = STD_i \times e^{0.0493 \times PP} \qquad \text{Equation 9}$$

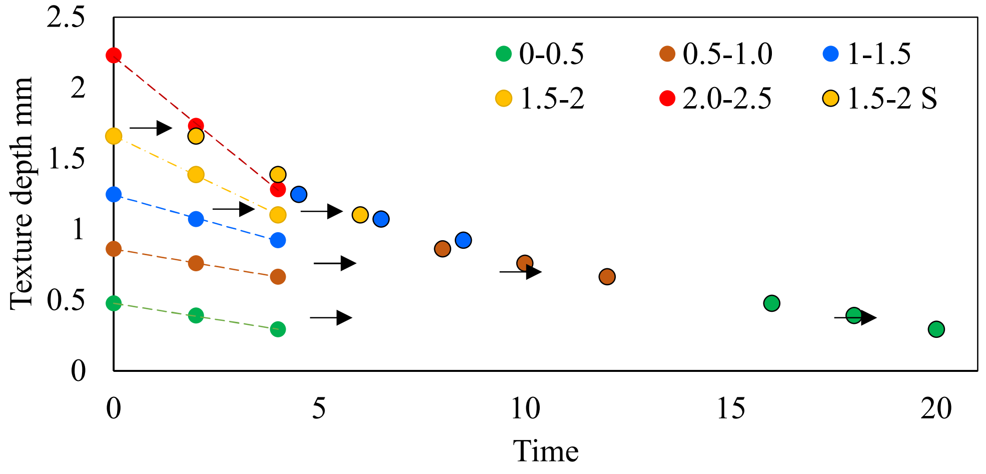

Figure 4. Illustration of the texture TDMC construction process (S stands for shifted data)

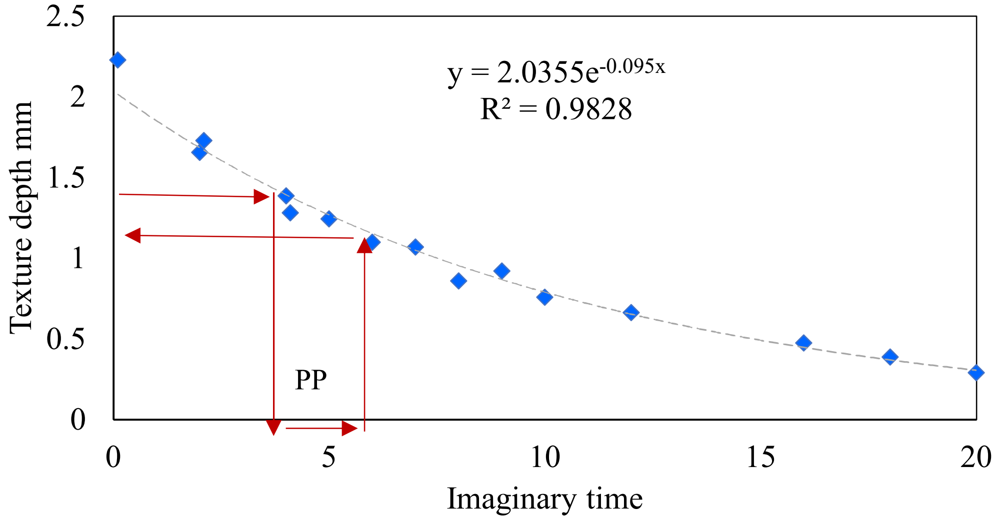

Figure 5. TDMC in the case of decreasing STD

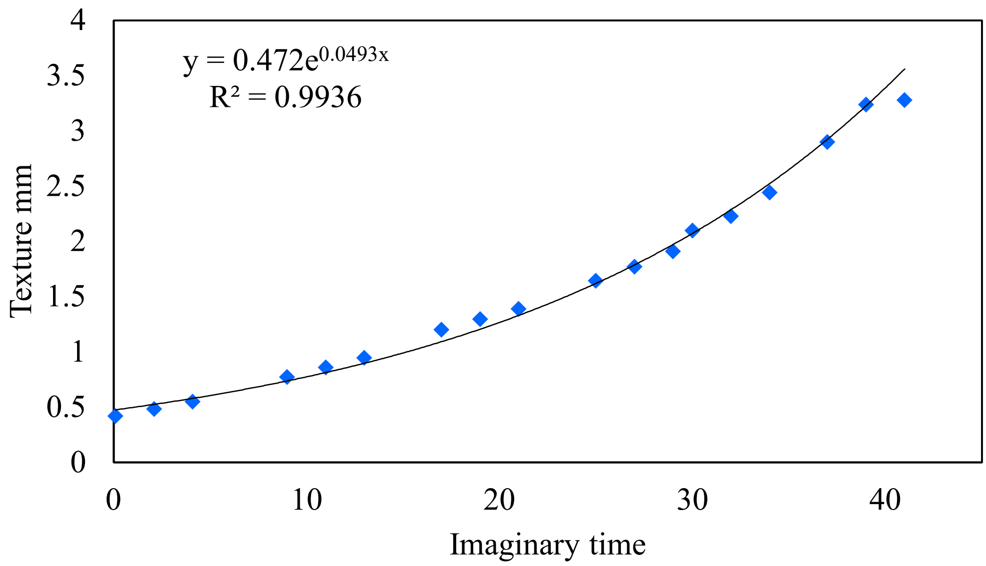

Figure 6. TDMC in the case of increasing STD

Model validation

The above models have been derived based on 2014-2018 data. To validate these models, the data in 2016 and 2018 have been used to predict the STD values in 2020, which have been compared with the actual measurements in 2020. The role of the data in 2016 and 2018 is to establish whether the analysed section is decreasing or increasing in texture, which can be accomplished using the following logic:

$$If\ STD_{2018} > STD_{2016}\ then\ the\ STD\ is\ increasing, otherwise\ it\ is\ decreasing$$

Admittedly, this is a basic analysis to assess whether the analysed section is exhibiting fretting or ravelling, and it may not be accurate as there is some error in texture measurements by the SCANNER method. This analysis, however, can be improved by coupling video recording and image processing principles to determine whether a road section is exhibiting fretting or ravelling or not, which reduces the number of the required inputs in the model to one STD measurement, but this is beyond the scope of this study.

Using the TDMC models shown in Equations 8 and 9, and 2016/2018 data the texture depth in 2020 was predicted, as shown in Figures 7, 8, and 9. The first figure shows the prediction results of sections exhibiting decreasing texture over time. It can be seen that the model can predict the texture to a very good accuracy with a correlation coefficient of 0.96 in this case. Figure 8 on the other hand shows the prediction results of texture depth in the case of sections exhibiting increasing texture over time. The performance of this model is not as good as the decreasing texture model as there is more scatter in the data. The correlation coefficient in this case was 0.77. Also, Figure 8 shows that the prediction model underestimates the texture in many sections. This is in fact a very reasonable result because the models implement the average deterioration rate in the prediction process, which makes texture decrease prediction more accurate as the deterioration mechanism is mainly related to aggregate polishing. On the other hand, texture increase is related to more sophisticated damage mechanisms such as fretting or ravelling, which are difficult to predict distress types. The last figure combines the results in the two cases; the overall correlation coefficient is 0.93, which shows that the developed models are reasonably reliable in predicting STD.

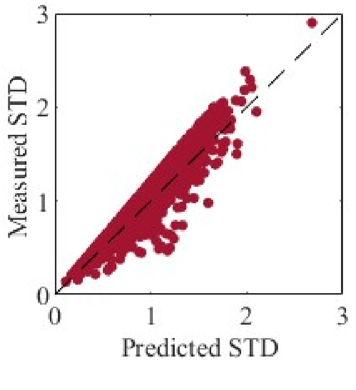

Figure 7. Validation of STD predictions in the case of decreasing texture

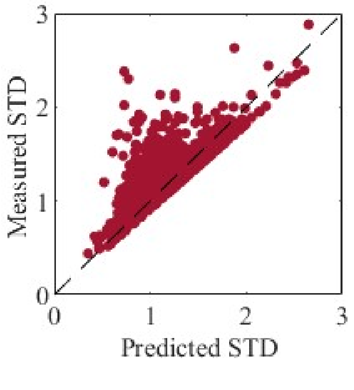

Figure 8. Validation of STD predictions in the case of increasing texture

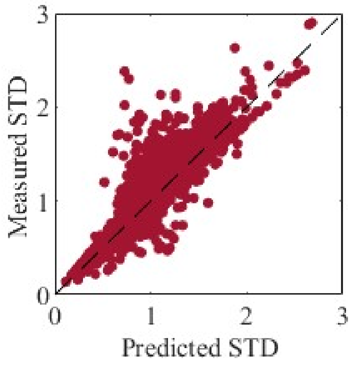

Figure 9. Overall validation of STD predictions.

Model application

The developed models can obviously be implemented in predicting STD. Implementing STD predictions to assess road network performance, however, can be extremely beneficial to highway authorities from a management point of view. STD has significant effects on different road aspects such as fuel consumption or collisions as discussed in the introduction section. Using STD predictions in assessing these aspects helps highways authorities to understand the influence of STD on the network performance and eventually making informed management decisions and strategic investment plans.

For instance, the relationship between pavement surface condition and collision risk has been investigated in several Transport Research Laboratory studies (Fairall et al., 2021; Parry & Viner, 2005; Wallbank et al., 2016). These studies have demonstrated that collision risk can be predicted based on road section type such as carriageways or junctions, and important predictors such as traffic flow, texture depth, or skid resistance. Since in this study, STD has been predicted for class A roads, then the following model developed by Wallbank et al. (2016) has been adopted:

$$Collision = Exp(Length + 0.86 \times \log(AADT) - 15.83 - 0.1 \times STD) \quad \text{Equation 10}$$

This model gives an indication of the risk of having a car accident per 100M vhe-km/year based on the considered section length, traffic flow and texture depth. It must be stated here that this model gives an indication of the collision risk rather than predicting an actual number of car accidents. The model has been used together with the developed STD models to predict the collision risk in 2020, 2024 and 2028 as shown in Figure 10. The traffic data has been downloaded from the Department for Transport traffic statistics data base (Department for Transport, 2023). This figure shows that sections with increasing STD will have less risk of collision because of the expected increase in skid resistance and a reduced risk of hydroplaning. On the other hand, the sections with decreasing texture depth will have more risk collisions over time because of the drop in skid resistance and increased risk of hydroplaning. Moreover, predicting and monitoring collision risk over time at the network level enables highway authorities to take strategic investment decisions to limit collision risk and improve safety on the network. This can be achieved by setting a threshold for the collision risk; for instance, keeping the risk below 0.215 (equivalent to 1.17 100M veh-km/year collisions on a 500 m road section with 10000 AADT and 0.5 mm STD) on any section, which can be used as an investigatory level to trigger further investigations and plan required maintenance.

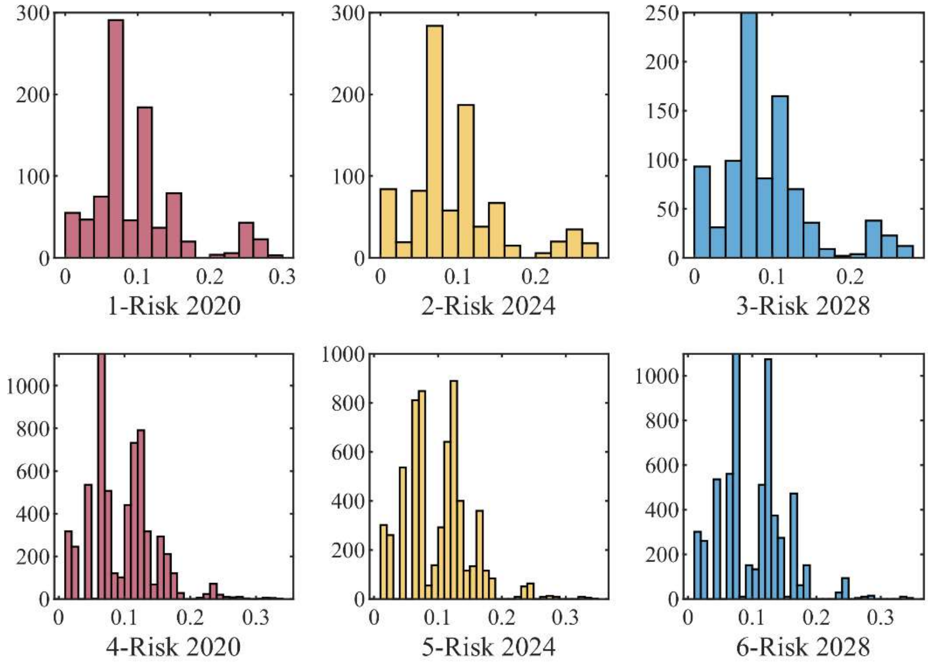

Figure 10. Collision risk results per 100M vehicle-km/year (1-3 show the collision risk results over sections with increasing STD, whereas 4-6 show the collision risk results over sections with decreasing STD).

Another application that has been considered in this study is the correlation between STD increase and pothole formation. As stated earlier, the increase in the STD is most likely a form of fretting or ravelling, which are defects can lead to pothole formation if left without maintenance (Abouelsaad & White, 2021; McRobbie et al., 2015; Scott et al., 2008). The relationship between STD and pothole formation has been quantified by (Abed et al., 2023a). This study shows that sections with STD of 2 mm or less have a low probability of 0.05 of developing a pothole, which means one out of twenty sections with this texture depth range will form a pothole. Sections with 2-3 mm STD have a medium probability of 0.1, and sections with STD of more than 3 mm have a high risk of 0.2. By implementing these figures together with the predicted STD data, the probability of pothole formation over the analysed sections has been predicted, as shown in Figure 11. This figure shows that sections with increasing STD will show an increased risk of pothole formation over time due to the increased risk of fretting and ravelling, which can lead to pothole formation, whereas sections with decreasing STD will have a low risk of pothole formation because these sections are unlikely to exhibit fretting or ravelling. Moreover, monitoring the risk of pothole formation at a network level, can help highway authorities to develop strategic plans and prepare investment schemes to limit the number of potholes on the network and enhance safety.

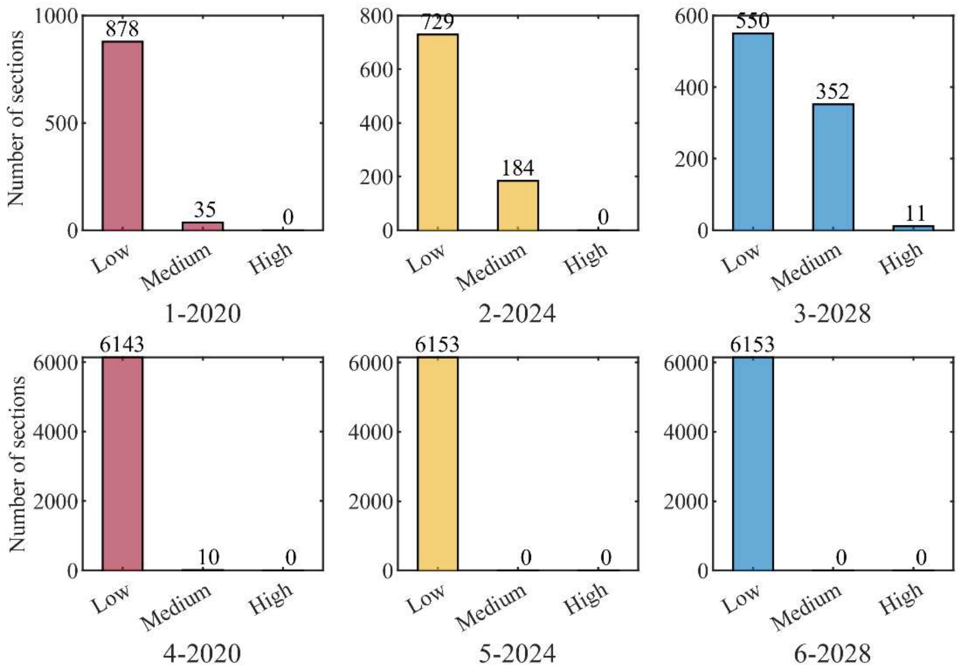

Figure 11. The results of the predicted pothole formation risk (1-3 show the number of sections with low, medium, or higher pothole formation risk over the sections with increasing STD, whereas 4-6 show the results over the sections with decreasing STD).

Conclusions

Road surface texture changes due to different factors such as friction between the surface and vehicle tyres, traffic volume, road geometry, and asphalt mix type and properties. The decrease or increase in the texture can lead to critical consequences such as reduced skid resistance, increased fuel consumption, increased noise, collision risk, and progressive distress types such as ravelling or potholes. Accordingly, it is extremely important to monitor texture depth to keep it with acceptable limits. In this study, simple texture depth prediction models have been developed using previous texture measurements collected by the SCANNER method. The models require input of the last two texture measurements and can be used to predict texture for extended period of times. The developed models have been used to predict texture depth on class A roads in Nottinghamshire; the validation results show that the models provide accurate texture predictions. Moreover, using available collision risk and pothole formation risk models, the collision risk and pothole formation risk over the investigated sections have been predicted. The results show that the developed approach can be a critical pavement management tool that is able to support highway authorities to make strategic plans and develop investment schemes to limit the negative impacts of road surface texture on the network performance. Within the limits of this study, the following major conclusions can be drawn:

1. The developed texture prediction models are built for a specific network with a certain condition. To implement these models, however, a “tailored” set of models should be developed based on the road class and other network properties following the same approach, which can significantly enhance the accuracy of the developed prediction method.

2. Texture decrease rate results show that sections with initial STD of more than 2 mm deteriorate at a rate that is almost double of the sections with initial STD of 1.5-2 mm. This suggests that limiting the initial STD to less than 2 mm will prolong the period of texture deterioration till it reaches the minimum allowable STD.
3. Using aggregates with good abrasion resistance in the surface layers of roads together with an optimum STD can enhance safety and reduce collision risk on roads. On the other hand, adopting preventive pavement maintenance approaches to prevent or delay fretting and ravelling can lead to critical benefits such as less fuel consumption and reduced risk of pothole formation.
4. The critical relationships between STD and network performance indicators such as collision risk or pothole formation means that STD prediction can play a critical role in network management by developing maintenance schemes designed to keep these indicators within acceptable limits. The threshold values of collision risk or pothole formation risk however should be thoroughly discussed and carefully selected as they have significant impacts on the way the network is managed.

Lastly, it must be stated that variability of texture deterioration was not considered in this study. The data analysed in this study however show that STD can increase or decrease at rates significantly higher or lower than the average deterioration rate. Therefore, it must be appreciated that the predictions made using the developed models are mean estimates that will enable pavement managers and highway authorities to make strategic investment decisions.

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Disclosure statement

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