The analysis and further development of a model for adjusting SCRIM skid resistance data for temperature and rainfall

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ABSTRACT

The skid resistance of a road pavement is not constant and fluctuates throughout the year due to seasonal variation. The SCRIM machine has been used in Ireland since 1985 to monitor skid resistance and is operated in accordance with standard HD28 published the National Roads Authority. A previous study has produced a model to correct for the seasonal effects of temperature with and without 30-day accumulated rainfall for two different asphalt surfaces, a surface dressing and hot rolled asphalt, using six years of control circuit data from 2005 to 2010.

The findings of this paper will include four more years of skid resistance data collected from 2011 to 2014 over 5.05 kilometres of the original 7.2 kilometre control circuit. The additional data was obtained using two SCRIM machines. The overall data set comprises 864 individual SCRIM runs with almost 87,000 50-metre skid resistance data points, and daily rainfall and temperature records, for the ten year period from 2005 to 2014.

The effect of seasonal variation has typically been understood to change from summer to winter depending on periods of rainfall or dry conditions. The previous work showed that temperature was a better indicator than 30-day accumulated rainfall to adjust for seasonal effects. This paper strives to develop an improved model to identify the seasonal factors that are responsible for the fluctuation in the sideway-force coefficient (SFC) based on ten years of data from 2005 to 2014 for one SCRIM machine, and also four years of pooled data from 2011 to 2014 for two SCRIM machines. A new parameter for 'testing season' is included in the analysis. The correlation between the predicted and measured pavement skid resistance is also examined.

Keywords: Asphalt, Friction, Skid Resistance, Surface dressing

1. INTRODUCTION

The Sideway-force Coefficient Routine Investigation Machine (SCRIM) has been used in Ireland since 1985 to monitor skid resistance. There are many factors that affect the skidding resistance of a pavement surface including wet or dry conditions, speed, seasonal variation, surface type, age and contamination of the road surface [(1)].

The effect of seasonal variation has typically been understood to change from summer to winter depending on periods of rainfall or dry conditions. A previous study has produced a model to correct for the seasonal effects in terms of temperature with and without 30-day accumulated rainfall for two different asphalt surfaces, a surface dressing and hot rolled asphalt, using six years of control circuit data from 2005 to 2010 [(2)]. The objective of this study was to continue the previous work using weather records and skid resistance data from 2011 to 2014 for two of the four sections of the control circuit that were used in the previous study. The length of test road amounted to 5.05 km of the original 7.20 km control circuit.

The additional data from 2011 to 2014 were obtained using two SCRIM machines. The previous work showed that temperature was a better indicator than 30-day accumulated rainfall to adjust for seasonal effects. This paper strives to develop an improved model based on ten years of data from 2005 to 2014 for one SCRIM machine, and also for four years of pooled data from 2011 to 2014 for the two SCRIM machines. A new parameter for 'testing season', either in season 'summer' or out of season 'winter', is included in the analysis. The correlation between the predicted and measured pavement skid resistance is also examined.

2. SCRIM OPERATION IN IRELAND

The SCRIM machine is currently operated in Ireland in accordance with HD28/11 - Management of Skid Resistance published by the National Roads Authority (NRA) [(3)]. Skid resistance is typically measured in the left-hand wheel path and the standard test speed is 50 km/hr. The sideway-force coefficient (SFC) is continuously measured with the average for each 10 metres section being recorded.

The two SCRIM machines used in this study are owned and operated by PMS Pavement Management Services Ltd. (PMS). The larger SCRIM (SCRIM-1) has a water tank capacity of 6,200 litres, and the second smaller SCRIM (SCRIM-2) has a water storage capacity of 3,600 litres. The SCRIM machines were operated, calibrated and maintained by PMS in accordance with specified standard conditions [(3) (4) (5)]. The SCRIM machines were serviced annually and had successfully passed the UK Highways England (formerly Highways Agency) accreditation trial at the TRL for each year of this study. Accordingly, the machine factors affecting SCRIM measurements, e.g. tyre wear, calibration, water flow and tracking, were minimised [(6)]. This study is limited to factors that are associated with test conditions, namely, surface type, temperature, rainfall and testing season.

To check and ensure consistency of the SCRIM machines throughout the year, the SCRIM machines are calibrated regularly on a long established (>10 years) control circuit that has established SFC values that would be expected at any time of year. Each year, a baseline calibration run is carried out on the control circuit immediately on the return from the UK correlation trial. Repeat runs on the control circuit are carried out throughout the year, typically on a weekly basis, to check that the SCRIM machines are operating within the expected ranges.

3. MODIFIED CONTROL CIRCUIT FOR THE STUDY

Figure 1 shows an overall view of the control circuit close to Galway city. The original four segments were Segment 1, a surface dressing (SD1), Segment 2, a surface dressing (SD2), Segment 3, a hot rolled asphalt (HRA3) and Segment 4, a hot rolled asphalt (HRA4). Since 2010, there has been a major modification to the control circuit with the completion of the M6 motorway from Galway to Dublin, which has interrupted Segments 1 and 3. As shown, an interchange connects the M6 to Segment 1, and a large-island roundabout on Segments 3 marks the end of the M6 on the approach to Galway city. Consequently, the remaining control circuit for the 2011 to 2014 data comprises Segment 2, a surface dressing, and Segment 4, a hot rolled asphalt surfacing, which are the same as the segments used in the previous study. The details of the two segments on the circuit are given in Table 1.

4. DEVELOPMENT OF THE MODEL

Multiple linear regression [(7)] was used to perform the statistical analysis of the data matrix to construct the prediction models in the study. The response variable was speed-corrected SFC and the input variables were surface type, average daily temperature, accumulated 10-day rainfall and testing season. The multiple linear regression and statistical data analysis was carried out using MINITAB and IBM-SPSS (Statistical Package for the Social Sciences), both widely used statistical packages for analysing data.

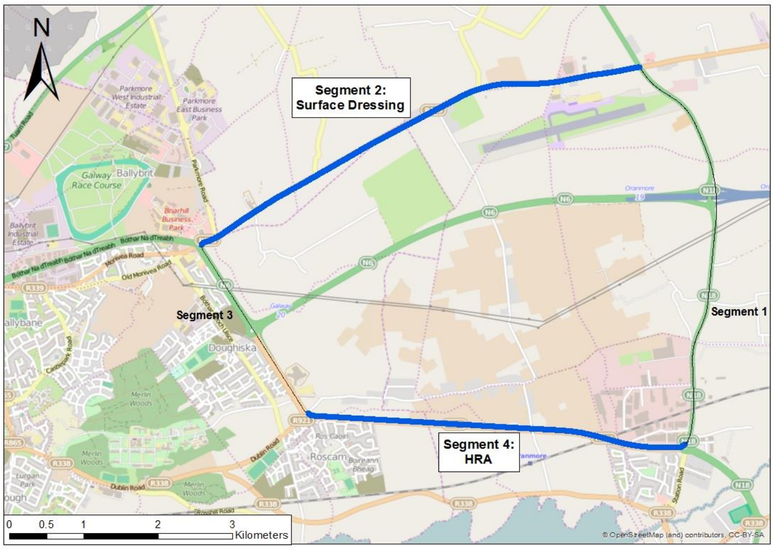

Figure 1: Overall View of the Control Circuit Showing Segments 2 and 4

Table 1: Segment Description for the Study

Segment Type	Segment	Road ID	Lane	Surface Type	Segment Length
SD2	2	R339	Westbound	Surface Dressing	2750 m
HRA4	4	R446	Eastbound	Hot Rolled Asphalt	2300 m

The analysis developed a mixed model with one fixed effect (surface type), one random effect (season), and two covariates (temperature and accumulated rainfall). The best model can be estimated by pooling the data from the two segment types, and adopting the approach of fitting one regression with an indicator variable for the two surface types [(7)]. The two different surface types, surface dressing (SD) and hot rolled asphalt (HRA), and testing season are converted into indicator variables by using 1 or 0 for the presence or absence of each factor. By using a mixed model, it was possible to perform the analysis in a way that adjusted for possible correlation between observations taken in the summer (May to September), and possible correlation between observations taken in the winter (October to April). It transpires that there was no difference between the models with and without adjustment for these possible correlations between observations. This result is consistent with the decision in the previous study to ignore possible within season correlations based on the residual diagnostic plots obtained in that study [(2)].

The regression model developed to take account of the effects of the different variables can be expressed in the standard form, $SFC = \beta_1 x_1 + \beta_2 x_2 \ldots \beta_p x_p$, as

$$\text{Speed Corrected SFC} = \beta_1\text{Segment-Type\_SD} + \beta_2\text{Segment-Type\_HRA} + \beta_3\text{Avg.\_Temp} + \beta_4\text{Accum.\_Rainfall} + \beta_5\text{Season}$$

where:
β - the effects of the regression coefficients of the corresponding variables
and using the indicator variables of 1 and 0 for the presence or absence of each surface type or season factors.
Segment-Type_SD = 1 if an observation is taken with SD and is 0 otherwise;
Segment-Type_HRA = 1 if an observation is taken with HRA and is 0 otherwise, and
Season = 0 if an observation is taken from May to September, and is 1 from October to April.

Hypothesis testing with a level of significance, α , equal to 0.05, corresponding to a 95% confidence interval, was used to determine whether a P-value was significant or not. The coefficient of determination, R^2, was used to report the percentage of variation in the data of the response variable that can be explained by the regression equation fitted to the data [(7)]. The VIF (variance inflation factor) was used to assess the effect of any potential multi-collinearity between the input variables on the fitted model with a value of 10 being a commonly used threshold. The predictive ability of the regression models were assessed using the PRESS (predicted residual sums of squares) statistic and the PMSE (prediction mean squared error) values. In addition, the appropriateness of each model was assessed by the usual residual diagnostics and other criteria.

5. COROLLARY

5.1. FURTHER ANALYSIS OF THE 2011 FITTED MODEL

The previous study produced a regression model, with an R^2 value of 72.1%, that could be used to correct for seasonal effects throughout the year using segment type, average daily temperature (ºC) and accumulated 30 days rainfall (mm) as input variables [(2)]. The full regression model was given by:

Speed Corrected SFC = 0.720xSegment-Type_SD1 + 0.751xSegment-Type_SD2 + 0.659xSegment-Type_HRA3 + 0.620xSegment-Type_HRA4 - 0.00815xAvg._Temp + 0.000057xAccum. Rainfall_30 eq. 1

The model without accumulated rainfall had an R^2 of 71.9% indicating that rainfall was not practically significant and that temperature was the major factor affecting the seasonal variation of skid resistance [(2)].

The diagnostic plots of the residual errors were deemed to be satisfactory for normality and constant variance of the error terms as indicated by the residual errors versus fitted values plot shown in Figure 2. However, further analysis of the magnitudes of the constancy of the residual errors showed that the variance of the residual errors for the surface dressing was twice the variance of the residual errors for the hot rolled asphalt. This result is not surprising considering the more rugous texture of a surface dressing with 100% shoulder-to-shoulder contact between the chippings, laid on a thin layer of binder with a chip spreader, and the more uniform 60% to 70% shoulder-to-shoulder contact of single-sized embedded pre-coated chippings spread with a mechanical spreader on paver-laid hot rolled asphalt. Because of the slight heterogeneity of the variance as evidenced in Figure 2, the analysis was rerun with transformations of the response variable. Using both the logarithm and the square root transformed 'Speed Corrected SFC' seemed to remove any heterogeneity and it is interesting to note that no change occurred in the P-values associated with the parameter estimates.

While the plot for residual errors versus observation order did not resemble unsatisfactory prototype textbook examples, there appeared to be an underlying trend in the order of the residual errors over the five consecutive years (2005 to 2009) as shown in Figure 3 due to the order of the residual errors of the four different segments being plotted sequentially, over time, instead of entirely over time. Figure 4 shows the same residual errors ordered against time order giving a significantly better diagnostic plot with good evidence of the independence of the residual errors.

It was not possible to properly model SFC dependence over time because the data points are not equally spaced. Typically, there are fewer SCRIM measurements during the months of December and January, as measurements should not be carried out at air temperatures below 5ºC [(3)], and also in February and April when the SCRIM machines are sent to the UK for the annual service and accreditation trial. Consequently, further analysis of the 2005 to 2009 data was carried out to model the effect of season by incorporating the additional input factor, Season, for testing season in the fitted model, Season = 0 for measurements made between May and September and Season = 1 otherwise. The regression model including season was given by:

Speed Corrected SFC = 0.702xSegment-Type_SD1 + 0.733xSegment-Type_SD2 + 0.641xSegment-Type_HRA3 + 0.601xSegment-Type_HRA4 - 0.00701xAvg._Temp + 0.000062xAccum. Rainfall_30 + 0.01028xSeason eq. 2

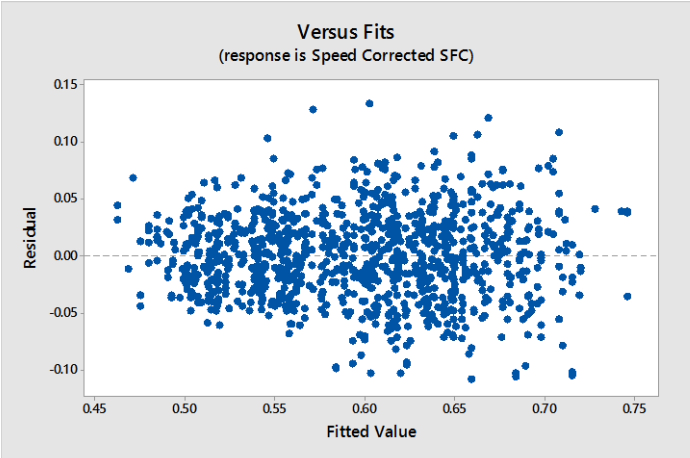

Figure 2: Residual Errors Versus Fitted Values (2005 to 2009 Model for 4 Segments)

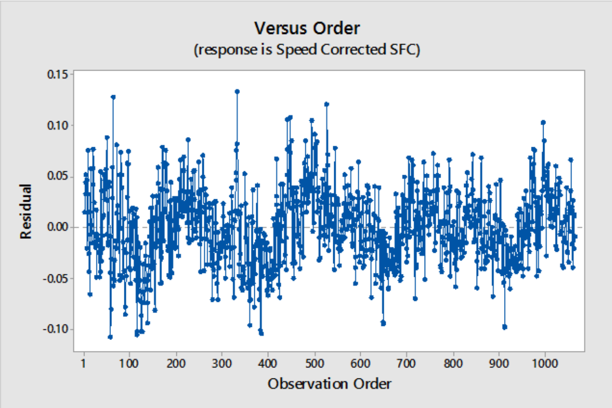

Figure 3: Residuals Versus Order by Segment Type

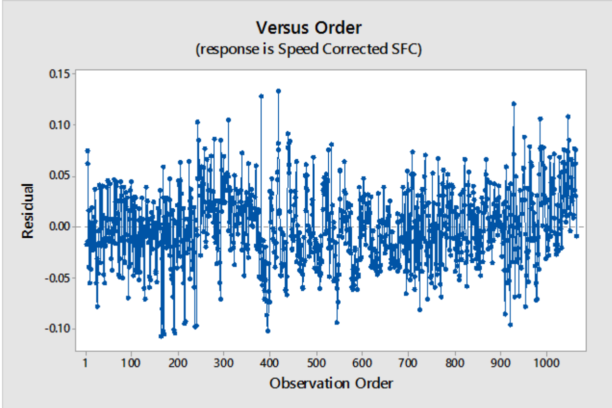

Figure 4: Residuals Versus Order by Time

The P-values associated with segment type and average temperature were 0.000+. The P-value for accumulated rainfall was 0.001 and, for season, it was 0.014. Therefore, all the input variables were significant. The VIFs were all very small (< 3.5) indicating that any correlation between the input variables does not have a negative effect on the analysis. However, the coefficient of 0.01028 for Season is considered to be of no practical significant when the other variables are present as it modifies the out of season speed corrected SFC by just +0.01. Similarly, the coefficient for accumulated rainfall of 0.000062 is very small. Hence, the effect of temperature still appears to be dominant.

5.2. APPROACH TO CALCULATING ACCUMULATED RAINFALL

In the 2012 paper [(2)], accumulated rainfalls for up to 60 days were calculated using Rainfall_1 as the rainfall on the day of the SCRIM test, Rainfall_2 as the sum of the rainfall on the day of and the day before the test and so on up to Rainfall_60. However, it was decided in hindsight that Rainfall_1 should be taken as the rainfall for the day before the SCRIM test. Accordingly, for this study, the effects on counting accumulated rainfall from the day of and the day before the SCRIM test were examined. In the analysis, the same values were obtained for the regression coefficients for segment type and average temperature, but for up to 30 days the coefficient for accumulated rainfall depended on the number of days of rainfall that were counted. Moreover, the P-values for the coefficients for segment type and temperature were consistently equal to 0.00+ (effectively zero), indicating that they were highly significant; and the P-values for the regression coefficients for the days of accumulated rainfall fluctuated for the first 30 days but remained consistently significant with a P-value of 0.00+ for accumulated rainfall greater than 30 days. A plot of the P-values obtained for each day of accumulated rainfall up to 60 days counted from both the 'day of' and the 'day before' the SCRIM test is shown in Figure 5 with a P-value of 0.00+ evident for 8, 9 and 10 days rainfall and for greater than 30 days rainfall. In addition, for up to the 30 day mark, the P-values for accumulated rainfall counted from the day before are almost always greater than the P-values for accumulated rainfall counted from the day of the test.

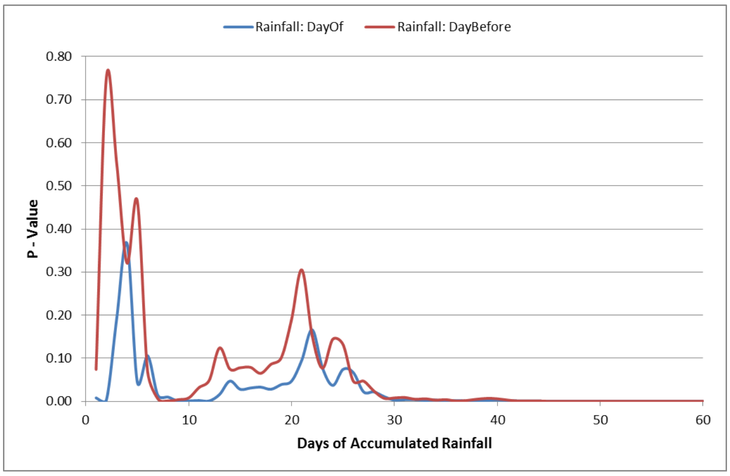

Figure 5: P-Values for Each Day of Accumulated Rainfall up to 60 Days

The coefficients of the regression models for speed corrected SFC versus segment type, average temperature and accumulated 30 days rainfall counted from the 'day of' [(2)] and the 'day before' the SCRIM test are shown in Table 2. In both models, almost the same values were obtained for the regression coefficients for segment type, average temperature and accumulated 30 days rainfall. The R^2 for both models was 72.1%.

As the P-values for 10 days accumulated rainfall are also 0.00+ (effectively zero), indicating that they were highly significant, the regression model was also developed for accumulated 10 days rainfall counted from the 'day of' and the 'day before' the test. The outputs are also given in Table 2. Again, almost the same values were obtained for the regression coefficients for segment type and average temperature as for the 30 day rainfall models with only a minor change to accumulated 10 days rainfall, which is not practically significant. The R^2 for the models accumulated 10 days rainfall were also 72.1%. Moreover, regression models developed using the geometric mean and harmonic mean of the 10 day and 30 day accumulated rainfalls had R^2 values of 72.3% indicating no improvement in the prediction model. Consequently, for this study using data from 2005 to 2014, the accumulated 10 days rainfall prior to making the SFC measurement counted from the day before the test was used as the input variable for accumulated rainfall in the regression models.

Table 2: Rainfall_10 and Rainfall_30 Regression Outputs for 2005 to 2009 Data

		Regression Coefficients						
Data Set	**Rainfall From**	**SD1**	**SD2**	**HRA3**	**HRA4**	**Avg Temp**	**Rainfall_30**	**R-sq**
SCRIM 1: 2005 to 2009	Day Of *	0.720	0.751	0.659	0.620	-0.008148	0.000057	72.1%
SCRIM 1: 2005 to 2009	Day Before	0.721	0.752	0.660	0.620	-0.008143	0.000051	72.1%
Data Set	**Rainfall From**	**SD1**	**SD2**	**HRA3**	**HRA4**	**Avg Temp**	**Rainfall_10**	**R-sq**
SCRIM 1: 2005 to 2009	Day Of	0.722	0.754	0.662	0.622	-0.008254	0.000124	72.1%
SCRIM 1: 2005 to 2009	Day Before	0.724	0.755	0.663	0.623	-0.008265	0.000103	72.1%
* Model Published in EE Congress 2012, Istanbul [2]								

6. RESEARCH DATA USED IN THE STUDY

6.1. TEMPERATURE AND RAINFALL DATA

The daily weather data of temperature (°C) and rainfall (mm) over the ten years for the study were provided from a weather station located on the campus of at the National University of Ireland, Galway (NUIG), which is 5km west of the SCRIM control circuit. Until December 2011, the weather station was located at ground level. Since then, it has been replaced with a new automatic weather monitoring station operated by the Informatics Research Unit for Sustainable Engineering (IRUSE) at NUIG. The new station was installed in June 2010 and is located on a rooftop one kilometre away from the previous station but almost the same distance from the control circuit. Accordingly, continued studies would have to take this new weather station data and relocation into account.

The duplication of weather records at the two weather stations for an 18-month period from July 2010 to December 2011 provided a means of correlating the two sets of weather data for making continuous comparisons with SCRIM measurements over the 10 years, 2005 to 2014. There was very good agreement between the daily temperatures recorded at each weather station and a very high R^2 value of 95.8%. On average, the IRUSE average daily temperatures were slightly higher than those for the ground station, as shown in Figure 6. The regression equation is given by:

IRUSE Temperature (°C) = 1.522 + 0.8873xGround Station Temperature (°C) eq. 3

The spatial separation of one kilometre had a more significant effect on the daily rainfall records, as evidenced by the plot of Ground Station versus IRUSE rainfall shown in Figure 7. The factors affecting the variations in the rainfall data in addition to the spatial separation included the different recording techniques, manual recordings of daily rainfall at vegetational ground level (Ground Station) versus automated recordings at rooftop level of rainfall data at hourly intervals (IRUSE). On average, the IRUSE daily rainfall data were slightly lower than those for the ground station. Incidentally, the R^2 value of 59%, which corresponds to a correlation of 77%, would be considered a reasonably good correlation based on the large sample size, albeit lower than the previous for temperature. Moreover, the objective of this part of the analysis was specifically to establish a regression equation for predicting the IRUSE rainfall from the ground level data for the 2005 to 2010 period. The regression equation without an intercept is given by:

IRUSE Rainfall (mm) = 0.8538xGround Station Rainfall (mm) eq. 4

These regression equations for temperature and rainfall were used to back-calculate the IRUSE temperature and rainfall from the ground station data for the years 2005 to 2010. Using this adjusted data, an overall pooled database based on IRUSE weather data for the 10 years from 2005 to 2014 was created for this study.

The temperature pattern over the ten-year period was reasonably similar from year to year excepting the very cold winters experienced in 2009 and 2010. For the 2005 to 2014 ten-year period, the maximum daily temperature reached was 30°C, the minimum temperature was -15°C and the overall average air temperature was 10.7°C.

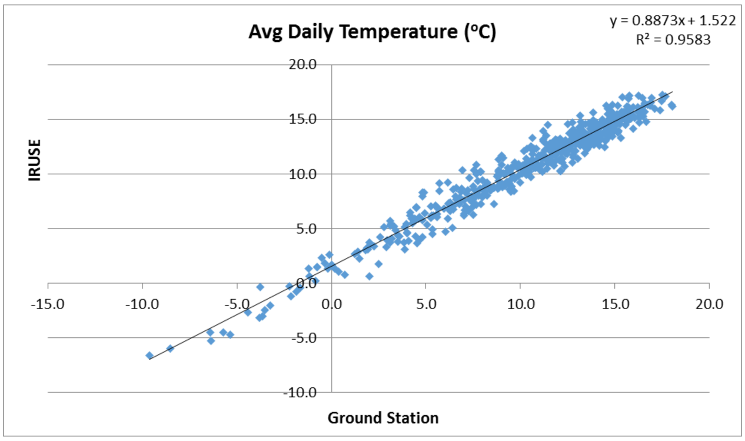

Figure 6: Comparison of Average Daily Temperatures from NUIG Weather Stations

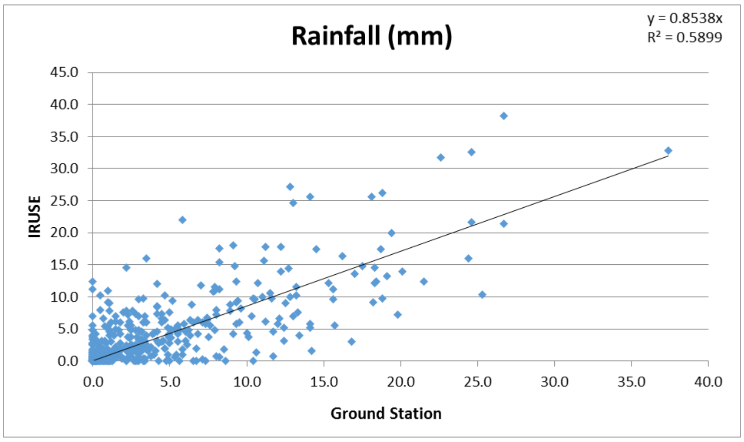

Figure 7: Comparison of Daily Rainfall from NUIG Weather Stations

Figure 8 shows a plot of the accumulative rainfall for each month for the ten-year period, 2005-2014. This figure illustrates the fluctuations in monthly rainfall both within and between years. Moreover, it illustrates the events of particularly wetter summers occurring in 2007, 2008, 2009 and 2012, and particularly drier summers occurring in 2005, 2006, 2013 and 2014. The occurrence of lower skid resistance in the earlier and later part of the year has also been noted in a previous study [8]. The average monthly rainfall for the 10 years is shown in Figure 9, with February, March and April proving on average to be the driest months. Figures 8 and 9 illustrate how the rainfall intensity can vary during the conventional summer and winter seasons and that the lowest accumulated rainfall do not necessarily occur during the summer months.

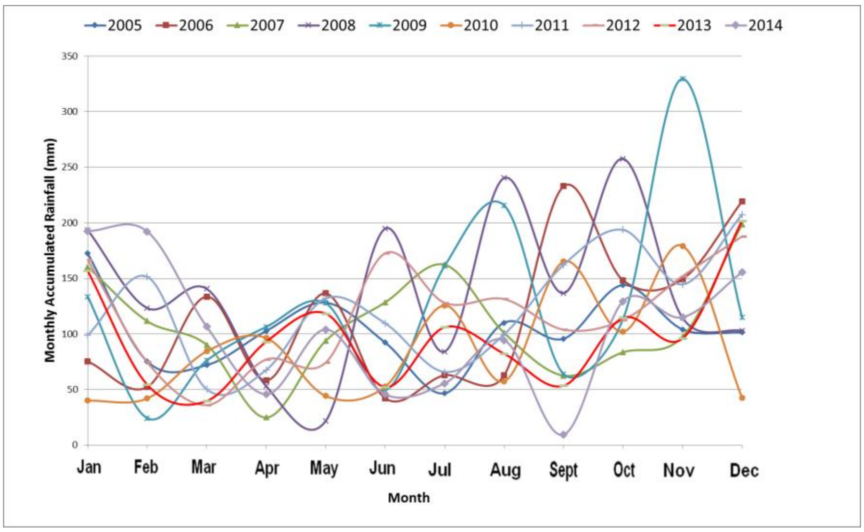

Figure 8: Monthly Accumulated Rainfall from 2005 to 2014

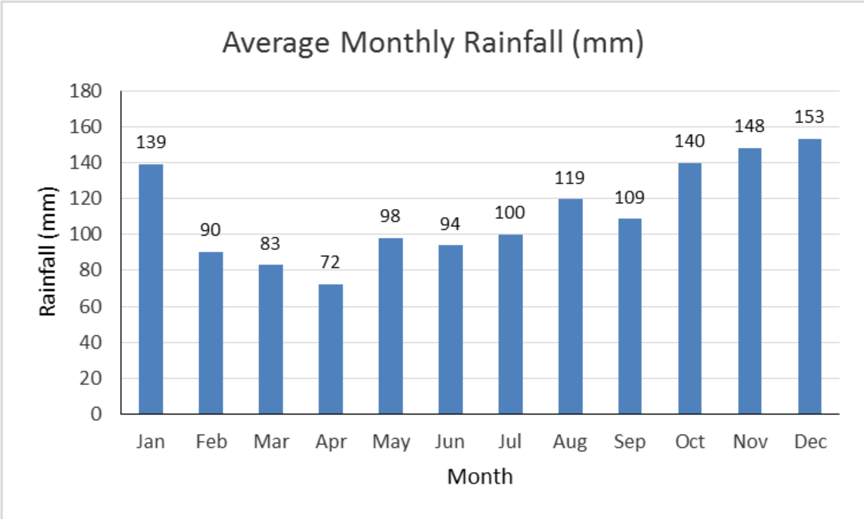

Figure 9: Average Monthly Rainfall for Ten-Year Period from 2005 to 2014

6.2. STABILITY OF THE CONTROL CIRCUIT

The road surface on each segment of the control circuit had been in place for over 15 years and there had been no maintenance treatment or overlay repairs carried out on these segments in that time. The mean summer SFCs from 2005 to 2014 for each segment are shown in Figure 10. The equilibrium ten-year average mean summer SFC on the surface dressing was 0.63 and, on the HRA it was 0.51, both with a standard deviation of 0.02. Therefore, it is reasonably assumed that an equilibrium level of skid resistance was maintained over the study period from 2005 to 2014, as the level of traffic flow remained reasonably constant [(9)].

Figure 11 shows the monthly fluctuation in SFC for the two segments over the ten years from 2005 to 2014. The typical cyclical pattern of lower skid resistance values in summer and higher values in winter is evident. However, the minimum SFC value can be attained early or late in the year (outside of the May to September summer season), for example 2007, 2010 and 2014. In these circumstances, the use of a seasonal adjustment based on time of year would lead to erroneous estimates of the SFC values.

The average SFC for the surface dressing ranged from 0.53 to 0.84 and the standard deviation was 0.05. The average SFC for the HRA ranged from 0.41 to 0.67 with a standard deviation of 0.05. The overall average SFC for the surface dressing was 0.67 and for the HRA it was 0.53.

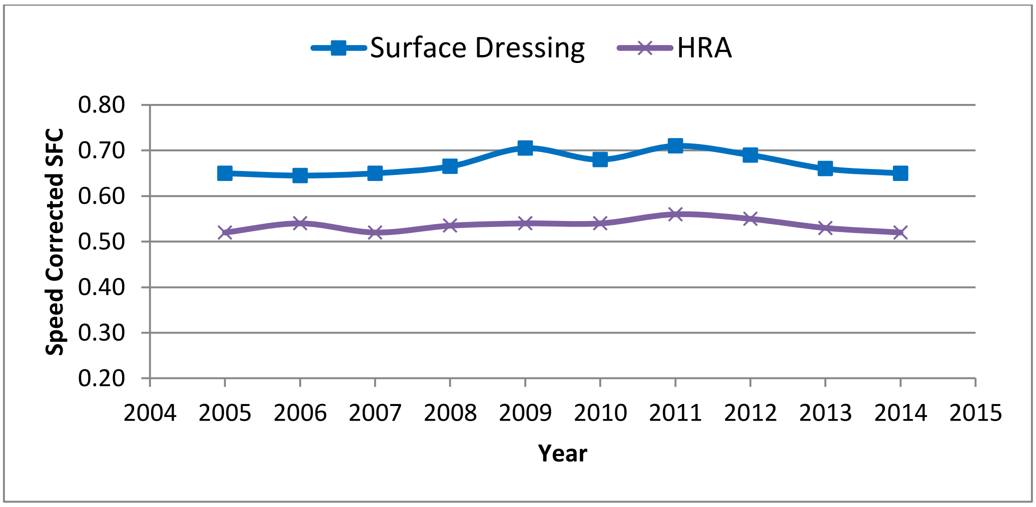

Figure 10: Mean Summer SFC by Year and Surface Type from 2005 to 2014

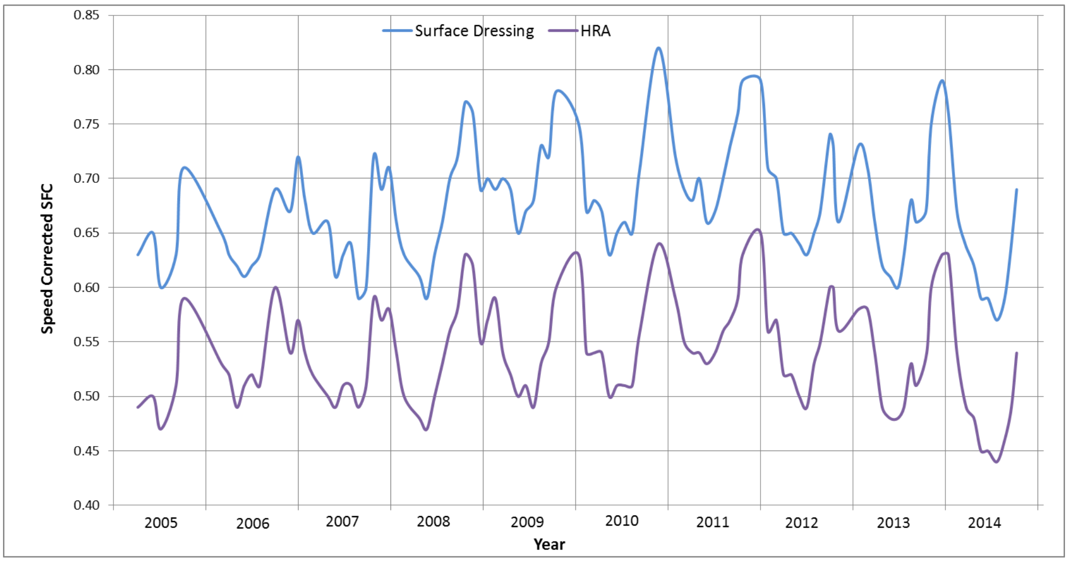

Figure 11: Monthly Average SFC by Year and Surface Type from 2005 to 2014

6.3. SCRIM DATA

The data for the study was collected using two SCRIM machines, the larger truck SCRIM-1 machine, which collected data from 2005 to 2014, and a second smaller truck SCRIM-2, which collected data from 2011 to 2014. The overall data comprised 864 individual SCRIM runs with 766 individual runs with the SCRIM-1 machine, and 98 individual runs with the SCRIM-2 machine. The overall data for the study comprised SFCs for almost 87,000 50-metre skid resistance data points (10 metre measurements averaged over 50 metre intervals). Due to the extremely large number of data points, the data were averaged for each run on each segment of the control circuit resulting in 1,516 segment SFC averages for SCRIM-1 and 194 segment SFC averages for SCRIM-2 in the regression analysis.

The overall average test speed for all runs was 50km/hr with a standard deviation of 1.1 km/hr. For consistency, the recorded SFC values were speed corrected to 50km/hr in accordance with NRA HD28/11 (3).

A comparison of the speed corrected SFC data from SCRIM-1 and SCRIM-2 based on 54 runs on the control circuit carried out on the same dates between October 2011 and November 2014 is shown in Figure 12. There was very good agreement between the SFCs with a high R^2 of 92.6%. The regression equation between the recordings is given by:

SCRIM_1 SFC = -0.0305 + 1.030xSCRIM_2 SFC　　eq. 5

There is no evidence that the underlying intercept differs from 0 (P-value = 0.233) or that the underlying slope differs from 1 (P-value = 0.4615).

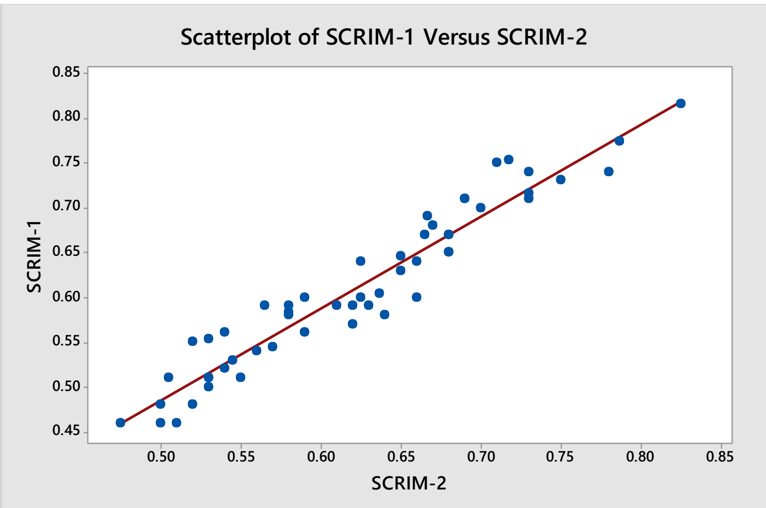

Figure 12: Plot of SCRIM-1 Versus SCRIM-2 Speed Corrected SFC for 2011 to 2014 Data

7. PERFORMANCE MODEL

Three models were developed in this study, one using 1516 data points from one machine SCRIM-1 from 2005 to 2014, a second based on pooling the two machines SCRIM-1 and SCRIM-2 with 969 data points from 2011 to 2014, and a third using the entire data set comprising 1710 data points.

Since the data set was large, it was possible to perform cross-validation; the models were developed by randomly selecting 85% of the data (model-building set) and then testing how good each of these models were by assessing how well they predicted the 15% omitted data (validation set) [(7)]. There was no evidence of interactions between the input variables segment type, average daily temperature (ºC) and accumulated 10 days rainfall (mm). The predictive abilities of the regression models were assessed using the PRESS statistic and the PMSE values. In addition, the appropriateness of each model was assessed by the usual residual diagnostics and other criteria.

7.1. MODEL FOR ONE SCRIM MACHINE USING SCRIM-1 DATA

The model with surface type, average temperature and accumulated 10 days rainfall was:

Speed Corrected SFC = 0.788xSegment-Type_SD + 0.651xSegment-Type_HRA - 0.010167xAvg. Temp + 0.000136xAccum. Rainfall_10 eq. 6

where:
Segment-Type_SD = 1 if an observation is taken with surface dressing and is 0 otherwise;
and Segment-Type_HRA = 1 if an observation is taken with HRA and is 0 otherwise.

The model has an R^2 of 81.7% and a PRESS statistic of 1.714. The results of the diagnostic tests are shown in Figure 13. The P-values associated with segment type and average temperature were 0.000+. The P-value for accumulated 10 days rainfall was 0.002. Therefore, all the input variables were significant. The VIF for all variables are very small ($\leq$ 1.01).

The scatterplot between the predicted speed-corrected SFC and the measured speed-corrected SFC for the validation data set is shown in Figure 14. The regression equation is:

Predicted Speed Corrected SFC = 1.00439 x Measured Speed Corrected SFC eq. 7

The PMSE value for the validation data set of 0.00141 is very close to the MSE based on the model-building data set of 0.00132. The value of 0.260 of the PRESS statistic is small. The PSME and PRESS statistic indicate that the developed regression model is a very good model for predicting the speed-corrected SFC. The t-value for testing the null hypothesis that the underlying slope is 1 versus the alternative that it differs from 1 is 1.063, which is not statistically significantly different from 0 with an associated P-value of 0.2889.

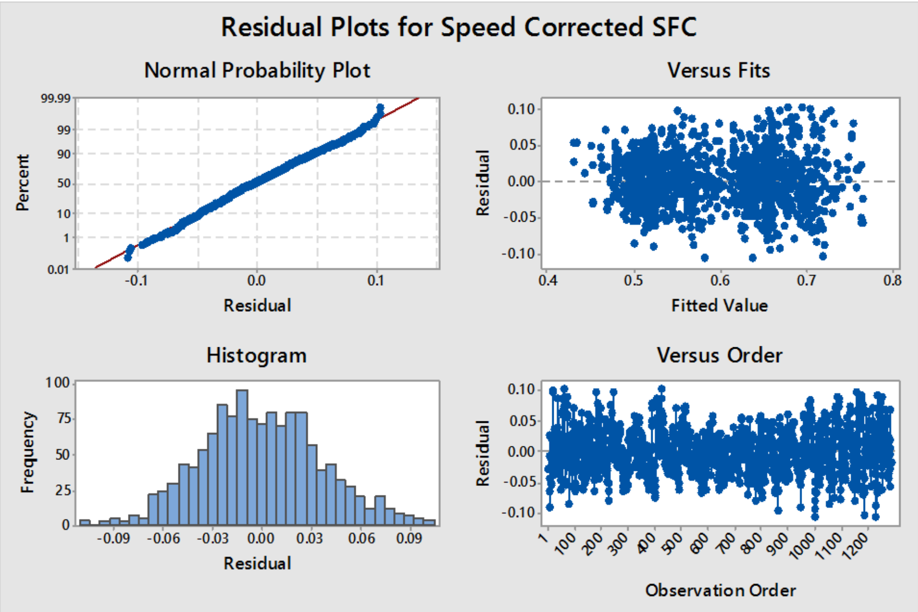

Figure 13: Residual Plots for Regression Analysis Using Segment Type, Average Temperature and Accumulated Rainfall_10 (2005 to 2014 SCRIM-1 Data)

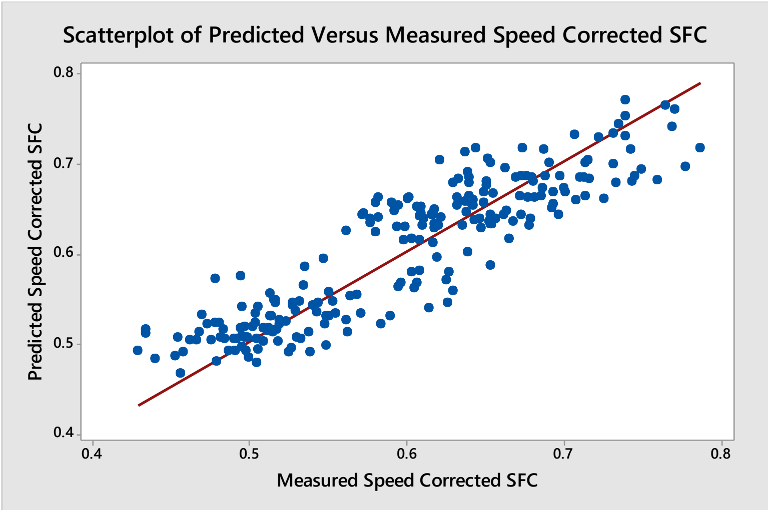

Figure 14: Plot of Predicted Speed Corrected SFC Versus Measured Speed Corrected SFC

Without accumulative rainfall as an input variable, the regression model is given by:

Speed Corrected SFC = 0.794xSegment-Type_SD + 0.657xSegment-Type_HRA - 0.010274xAvg. Temp eq. 8

This model has an R^2 of 81.6% and a PRESS statistic of 1.725. The P-values for the parameter estimates were all 0.000+, indicating that the input variables were all significant. This simpler model without accumulated rainfall could be used to correct for seasonal effects using the regression coefficient of -0.010274 for average daily temperature (ºC) alone. The regression equation between the predicted speed-corrected SFC and the measured speed-corrected SFC is:

Predicted Speed Corrected SFC = 1.00415 x Measured Speed Corrected SFC eq. 9

The PMSE value for the validation data set of 0.00140 is very close to the MSE based on the model-building data set of 0.00133. The PRESS statistic value of 0.260 is small. The PSME and PRESS statistic indicate that the developed regression model without rainfall would also be a very good model for predicting SFC. The t-value for testing the null hypothesis that the underlying slope is 1 versus the alternative that it differs from 1 has an associated P-value of 0.3137. The closeness of the PMSE values suggest that the two candidate models (with and without rainfall) perform comparably in terms of predictive accuracy. It is equally arguable that this simpler behavioral model could be used to correct for seasonal effects. These findings would indicate that temperature is the major factor affecting the SFC.

The best model with accumulated rainfall only and without including temperature was:
Speed Corrected SFC = 0.655xSegment-Type_SD + 0.518xSegment-Type_HRA + 0.000301xAccum._Rainfall_10 eq. 10

This model has an R^2 of 65.3% and a PRESS statistic of 3.253. The lower R^2 indicates that this model is not as good as the previous models that include temperature. The MSE value based on the model-building set of 0.00251 is greater than for the other fitted models indicating reduced predictive ability.

The introduction of testing season as a random effect in the regression equation was also investigated as a means of removing the effect of possible seasonality. The regression analysis of the mixed model including surface type, average temperature, accumulated 10 days rainfall and season showed that, as before (5.1 above), season was not practically significant when the other input variables are present.

7.2. MODEL FOR TWO SCRIM MACHINES USING SCRIM-1 AND SCRIM-2

The model for the two SCRIM machines based on surface type, average temperature and accumulated 10 days rainfall is:

Speed Corrected SFC = 0.798xSegment-Type_SD + 0.659xSegment-Type_HRA - 0.010667xAvg. Temp + 0.000223xAccum. Rainfall_10 eq. 11

The model has an R^2 of 82.1% and a PRESS statistic of 1.153. The results of the diagnostic tests are shown in Figure 15. The P-values associated with segment type, average temperature and accumulated 10 days rainfall were all 0.000+, indicating that all the input variables were significant. The VIF for all input variables were all small (≤ 1.15).

The scatterplot between the predicted speed-corrected SFC and the measured speed-corrected SFC is shown in Figure 16. The regression equation is:

Predicted Speed Corrected SFC = 0.999xMeasured Speed Corrected SFC eq. 12

The PMSE value for the validation set is 0.00144 which is very close to the MSE of 0.00139 based on the model-building data set. The value of the PRESS statistic is small at 0.165. The t-value for testing the null hypothesis that the underlying slope is 1 versus the alternative that it differs from 1 has an associated P-value of 0.8430. The PSME and PRESS statistic indicate that the developed regression model using the data from the two SCRIM machines is a very good model for predicting the speed-corrected SFC.

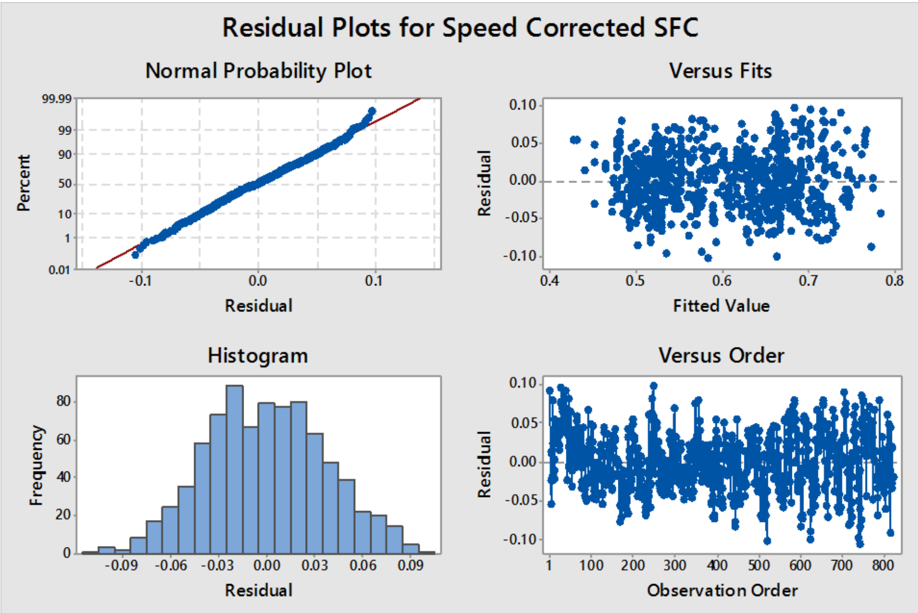

Figure 15: Residual Plots for Regression Analysis Using Segment Type, Average Temperature and Accumulated 10 days Rainfall Based on Data From Two SCRIM Machines

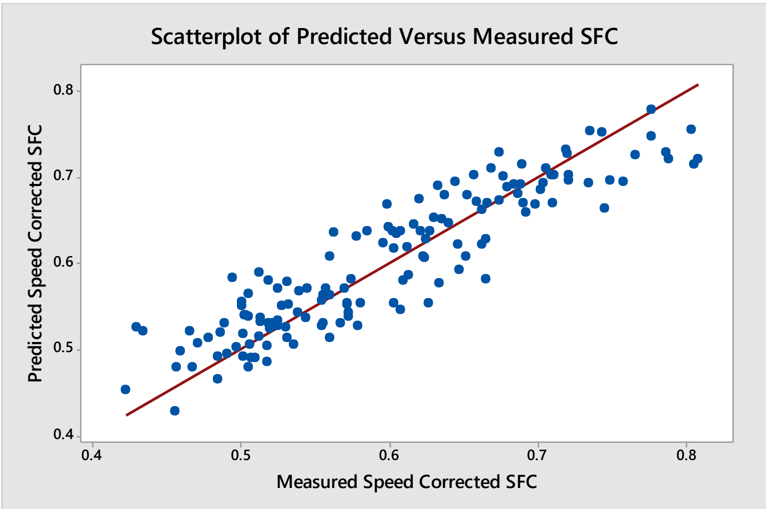

Figure 16: Plot of Predicted Speed Corrected SFC Versus Measured Speed Corrected SFC Using Model Developed From Two SCRIM Machines

Without accumulative rainfall as an input variable, the regression model is given by:

Speed Corrected SFC = 0.812xSegment-Type_SD + 0.673xSegment-Type_HRA - 0.011167xAvg. Temp eq. 13

The model has an R^2 of 81.8% and a PRESS statistic of 1.167. The P-values associated with segment type and average temperature were 0.000+, indicating that all the input variables were significant. The VIF values were all small at 1.00.

The regression equation between the predicted speed-corrected SFC and the measured speed-corrected SFC is:

Predicted Speed Corrected SFC = 0.9987xMeasured Speed Corrected SFC eq. 14

The PMSE value for the validation data set of 0.00151 is very close to the MSE of 0.00141 based on the model-building data set. The PRESS statistic value of 0.175 is small, also suggesting very good predictive ability. The t-value for testing the null hypothesis that the underlying slope is 1 versus the alternative that it differs from 1 has an associated P-value of 0.8106. The values indicate that this regression model based on the data from the two SCRIM machines and temperature only is also an excellent model for predicting the speed-corrected SFC. In addition, the closeness of the PMSE values for the two candidate models (with and without rainfall) suggest that both models perform comparably in terms of predictive ability.

7.3. MODEL FOR ENTIRE DATA SET

Following the validation of the regression models, the entire data set obtained using both SCRIM machines, and comprising 1710 cases from 2005 to 2014, was used to develop the final regression model. The final model based on surface type, average temperature and accumulated 10 days rainfall is:

Speed Corrected SFC = 0.790xSegment-Type_SD + 0.653xSegment-Type_HRA - 0.010286xAvg. Temp + 0.000152xAccum. Rainfall_10 eq. 15

The model has an R^2 of 81.4% and a PRESS statistic of 2.346. The P-values associated with segment type, average temperature and accumulated 10 days rainfall were all 0.000+. Therefore, all the input variables were significant. The MSE value based on the entire data set is 0.00137.

Without accumulative rainfall as an input variable, the final regression model is given by:

Speed Corrected SFC = 0.797xSegment-Type_SD + 0.661xSegment-Type_HRA - 0.010448xAvg. Temp eq. 16

The model has an R^2 of 81.3% and a PRESS statistic of 2.365. The P-values associated with segment type, average temperature and accumulated 10 days rainfall were all 0.000+, indicating all the input variables were significant. The MSE value for this model is 0.00138 which is very comparable to the model with temperature and accumulated rainfall.

8. CONCLUSIONS

This study has produced a linear regression model for relating SFC skid resistance to the input variables surface type, average temperature on the day of testing and 10-day accumulated rainfall based on SCRIM measurements made over ten years for a surface dressing and a hot rolled asphalt. The research included regression analyses of speed corrected SFC against surface type, average temperature and accumulated rainfall for up to 60 days. The analysis consistently obtained the same values of the regression coefficients for the surface type and average temperature, but the coefficient for accumulated rainfall depended on the number of days rainfall that were counted. Moreover, the P-values for the coefficients for surface type and temperature were consistently equal to 0.00+ (effectively zero) indicating that these variables were highly significant. The P-values for the regression coefficients for the days of accumulated rainfall fluctuated for the first 30 days but remained consistently significant with a P-value of 0.00+ for accumulated rainfalls greater than 30 days, and had a value of 0.00+ also for accumulated rainfalls of 8 to 10 days. Consequently, because there was no difference in the significance of the P-values for 10 days and 30 or more days, the accumulated rainfall for the 10 days prior to making the SFC measurement was used as the rainfall parameter included in the regression model.

For ten years of records using one SCRIM machine and four years of records using two different SCRIM machines, similar regression models for temperature, accumulated rainfall and testing season were obtained. The resulting R^2 value was 81.7% for the one-SCRIM model, and 82.1% for the two-SCRIM model. The validation of the developed models showed that both models had excellent predictive ability as observed by the small magnitude of the PRESS statistic values. Of the input variables, surface type and temperature were by far the dominant contributors. Testing season did not have practical significance when the other input variables were present in the model. Based on the entire data set, the final regression model could be used to correct for seasonal effects throughout the year using the regression coefficients of -0.01 for average daily temperature (ºC) and 0.00015 for accumulated 10 days rainfall (mm).

The regression models for surface type and average daily temperature, without accumulated rainfall, are also presented. The resulting R^2 values were very close at 81.6%, for the one-SCRIM model, and 81.8% for the two-SCRIM model. The models also had excellent predictive ability. Accordingly, it is equally arguable that this simpler behavioral model could also be used to correct for seasonal effects using the regression coefficient of -0.01 for average temperature (ºC) alone. These findings would indicate that temperature is a major factor affecting the seasonal variation of skid resistance.

There was no discernable difference between the PRESS statistic values obtained for the various models that were developed and tested based on the input variables of surface type and average daily temperature, with and without accumulated rainfall. In addition, the closeness of the prediction mean squared error values suggest that the various models perform comparably in terms of predictive accuracy.

9. ACKNOWLEDGEMENTS

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