Improving Decision Making and Works Program Development with Continuous Network Strength and Condition Data (IDM) - Stage 3– Final Report

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Final

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Summary

The current WARRIP 'Improving decision making' (IDM3) project was designed to model and validate rutting deterioration prediction on Western Australian roads to provide additional and more tangible benefits to Main Roads Western Australia (MRWA) through more reliable and accurate rutting prediction.

Task 1 of the project included the creation of performance matrices of road segments taking the full MRWA network into account to demonstrate similar rutting progression trends with time. The matrices were referenced by the rutting performance (rate of distress) of the road sections.

Findings from the analysis under Task 1 are as follows:

- Nearly 14% of the network has a rutting progression rate of more than 1 mm/year.
- Similar rutting distributions across the regions were observed although higher values were observed for the Kimberley region. It should be noted that approximately 66% of the road length in the Kimberley region met the analysis criteria, and this might affect the findings.
- The expected relationship between traffic volume and rut progression was found with the more heavily trafficked roads displaying lower average rut progression rates. Therefore, they represent a higher proportion of the road length in the lower rut progression bands. Roads carrying higher volumes of traffic are built to a higher design standard. An example are road links in the MI (Metro) region which had a lower rate of deterioration and a higher proportion of the road length in the lower rut progression ranges than other link categories.
- The average rutting progression values are similar across pavement age bands. However, pavements constructed after 2014 show higher average rut progression while very old pavements show reduced rut progression. This could be due to the 'survivor' effect of old and strong pavements.
- The 'Very Poor' preventative maintenance indicator (PMI) values, that are reflective of the oxidation of the sprayed seal surfacing, are associated with a higher portion of road length in the higher rut progression bands for selected MRWA regions.
- Rainfall does not have a significant influence on rut progression rates. However, the wetter areas of the Great Southern and South-West regions display a slightly increased portion of road length in the more than 1 mm/year rut progression range.
- For all traffic ranges, the higher Thornthwaite Moisture Index (TMI) values are generally associated with a larger portion of road length in the higher rutting progression bands. This observation also holds true at regional levels except for the Metro and the Pilbara regions.

Findings from Task 1 were used as inputs for Task 2, the development of a rut progression model for WA. The outputs from this modelling task are:

- a total rutting progression model for the full MRWA network
- refined total progression rutting models for each MRWA road link category.

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Models were developed using the full network MRWA data, including independent variables such as pavement strength, traffic, pavement age, etc. and their combinations. However, these models did not contain the whole possible spectrum of independent variables, such as different traffic ranges and pavement strength levels. About 66% of the analysed data samples had a surface deflection less than 600 micron. A vast majority of these samples also sat within the low traffic range of annual Equivalent Standard Axles (ESA) less than 1 million. Only 7% of the analysed sample had a maximum deflection greater than 1,000 microns. There were hardly any samples with a high/moderate combination of deflection (> 1,000 micron) carrying moderate/high traffic (annual ESA of 1 million). Hence the model should only be applied within the conditions it was developed and should not be extended for conditions such as:

- pavements with low strength (deflection > 1,000 micron) carrying moderate to high traffic (annual ESAs over 1.5 million) where no examples were available
- pavements with moderate strength (deflection in between 800–1,000 micron) carrying moderate to high traffic (annual ESA > 1 million) where only a low number of examples were available.

Task 3 involved testing and validation of the developed models against observed deterioration. This was done using datasets used in the model development (training data), and also with an independent dataset not used during model development (test data). Differences were observed between the collected and predicted rutting values using both datasets. This was expected as the predictive power of the network-level rutting model was a moderate goodness of fit to the data (adjusted $r^2 = 0.46$).

Under Task 4, the predicted rate of change in rutting using the newly developed model for 2 WA regions was compared against the rate of change from the observed data. For all the years compared, the predicted rutting across different progression bands using the developed model were close to the actual observed data.

Implementation of the new model in MRWA's dTIMS (Deighton's Total Infrastructure Management System) PMS tool is required to determine the differences of predictive capability of the models across the MRWA road network. A strategic network analysis in dTIMS is also required to quantify the benefits from the use of the developed model. The anticipated benefits from using the developed rut model include:

- overall lowering of the total transport cost due to accurate targeted intervention
- lowering of the risk of inaccurate prediction by increasing the accuracy in rutting prediction.

As a part of this project, the following additional developments are also proposed for MRWA's consideration:

- Further refinement of the developed model(s) to address significant changes in heavy vehicle loading and pavement conditions building on the outcome of the parallel Austroads project AAM6214.
- Development of models for other road deterioration parameters – e.g., roughness to provide a full suite of improved WA-specific models.

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1 Introduction

1.1 General

Using the 2018 Traffic Speed Deflectometer (TSD) condition data, Stage 1 of the WARRIP project 'Improving decision making with continuous network strength and condition data (IDM) project' developed region specific Rehabilitation Identification Formulas (RIFs). Stage 1 revealed the need for further refinement of the RIFs to enhance Main Roads Western Australia (MRWA) rehabilitation work scoping and programming. This was developed further under Stage 2 of the IDM project.

As a part of the IDM2 project, rutting classification was extracted for the entire MRWA network and the relationship between rut types and other parameters (rut width, remaining life, rutting rate of progression, rut radius, rut depth, etc.) were explored. An updated road link category was subject to multi-variate logistic linear regression (MVLR) analyses which considered additional independent variables such as the Maintenance Management Information System (MMIS) defect intensity, remaining pavement life, lower soil moisture content, TSD slope velocity parameters, and climate information. Outputs from the Stage 2 analysis also showed that, for all road link categories, maximum rutting remained one of the most significant factors in the identification of rehabilitation in addition to variables such as MMIS, heavy vehicle numbers, and TSD slope velocity parameters.

The MLVR approach allowed the initial identification of structural-based rehabilitation candidate sites. Other candidate sites were identified based on functional distress where the maximum deflection limits were not exceeded. This represented a significant potential saving to MRWA that avoided over-investment in rehabilitation where only functional distress needs to be addressed.

Findings from both Stage 1 and Stage 2 showed that rutting was one of the main contributing factors to the initiation of rehabilitation. The purpose of Stage 3 of the project was, therefore, to model and validate rutting deterioration on MRWA-managed sealed roads to provide additional and more tangible benefits to MRWA through more reliable rutting prediction.

1.2 Scope of the Project

The scope of the IDM3 project included the following:

- Development of WA-specific rutting deterioration models which account for actual network condition attributes and types and levels of distress to provide a more rigorous basis upon which long term maintenance and rehabilitation funding needs can be projected and justified. The rutting deterioration model(s) should account for contributions from structural attributes, pavement type, traffic, historic network condition and maintenance inputs, and the primary modes of distress and their root causes.
- Testing and validation of the developed model(s) to compare the predicted rutting values with the measured rutting values. Several site inspections would be undertaken to confirm the results if required. An in-depth review of performance of the rut model(s) would also be undertaken for 2 selected Western Australian (WA) regions.

1.3 Task under the Project

The project consists of 6 broad tasks:

- Task 1: Creation of rutting performance matrices
- Task 2: Development of a rutting model(s)
- Task 3: Testing and validation of the rutting model(s)
- Task 4: Undertaking in-depth review of the performance prediction of the rut model(s) for 2 MRWA regions.

- Task 5: Presentation and demonstration of the rutting model(s)
- Task 6: Preparation of the final report.

This report summarises all the different tasks completed for the project delivery. New sections were added to the report after the delivery of each task.

Section 2 summarises the findings from the Task 1 of the project. The approach used as well as outputs from the performance matrix development work are summarised in the following sections.

Section 3 outlines the rutting model(s) developed as a part of Task 2. The sample selection process as well as IBM SPSS Statistics analysis outputs are discussed.

Section 4 outlines the validation of the developed rutting model(s) using both training and test datasets

Section 5 summarises the comparison of observed and predicted total rutting progression for two selected regions.

Section 6 summarises the overall findings from the project.

2 Task 1 – Development of Performance Matrices

2.1 General

Task 1 included the creation of performance matrices of road segments that demonstrate similar rutting progression trends with time, taking the full MRWA network into account. The matrices were referenced by the rutting performance (rate of distress) of the road sections. The output from Task 1 was expected to enable MRWA to identify pavement sub-networks that demonstrated significantly different rutting deterioration rates, both higher and lower than the mean, to allow more precise targeted inspection regimes and investments to be made in terms of the future planning for both functional- and structural-based rehabilitation.

2.2 Data for Analysis

2.2.1 Data Requirements

At the commencement of the project, the Australian Road Research Board (ARRB) submitted a data requirement template to MRWA to supply the required historical pavement condition data, traffic, inventory, and other ancillary information. MRWA supplied historical pavement condition data (roughness, rutting) from 2007 to 2016, which was collected bi-annually. A full TSD dataset, including deflection information, was also supplied for the years 2018 and 2020. ARRB used the datasets to develop performance matrices. For Task 1, the maximum of the 75th percentile rut depth value across the wheel paths was used in the analysis as requested by MRWA.

2.2.2 Review of the Supplied Data

Historical data included the following:

- The 2007 to 2016 dataset, including roughness and rutting information for each segment.
- No MMIS information was available in the 2007 to 2014 dataset.
- The latest (up to 2021) pavement wear and surface year information was included with each historical dataset.
- The latest annual average daily traffic (AADT) (up to 2017) was included with each historical dataset.

During data processing, ARRB also created additional calculated columns for performing the analysis. These included the:

- uniqueID for each segment
- Thornthwaite Moisture Index (TMI) and its range
- AADT range
- rainfall range
- pavement age range
- seal life
- 75th percentile rut depth (maximum of 75th percentile rut depth value across both wheelpaths).

The pavement age data provided useful information on the year of the last structural rehabilitation. However, for some reviewed segments, the selected rutting values (maximum of 75th percentile of left and right side, inner wheelpath (IWP) and outer wheelpath (OWP)) showed a significant reduction between adjacent data years, indicating a possible treatment that was not reflected in the reported pavement year. An example is shown in Figure 2.1 where a reduction in rut values was observed between 2009 to 2012, indicating some form of maintenance. However, the 'pavement age' year is recorded as 2000. Another explanation for such discrepancies could be a consequence of MRWA using different data collection suppliers and measuring equipment over time.

Figure 2.1: Rut depth reduction with possible effect of maintenance

Road_No	Cway	SLK_Start	SLK_End	ElementID	TrueSLK_S	TrueSLK_E	SurfYr	PAOR_PAVE_YE	2007	2009	2012	2014	2016
H001	L	0	0.1	H001_L_0	0	0.1	2000	2000	2.92	3.03	1.82	4.27	3.35

This issue was examined further when selecting segments for the calculation of rutting progression over time.

2.3 Segment Selection for Rut Progression Calculation

Ideally, the entire MRWA network should be used for calculating the rate of rutting progression. However, from 2007 to 2020, different types of treatments were applied which could either reset the rut depth and/or slow the rate of rutting progression. Hence, for rut progression calculations, segments needed to be selected in a manner to exclude the effect of any possible maintenance. The approach adopted for this is outlined below.

2.3.1 Steps in Segment Selection

Segment selection involved the following steps:

1. Merging the datasets – the 2007 to 2020 datasets were merged and matched for identical segments.
2. Matching identical segments in different years – about 193,000 segments were matched in all years.
3. Excluding segments with no rutting data – about 10,000 segments did not have rutting data in any year.
4. Excluding and discarding the segments where reductions in rutting were observed.
5. For any segment, the years where there was no rutting data value were recorded as zero (i.e. not collected) and ignored.
6. Only segments with data in at least 3 consecutive collection years were used.
7. Segments with recorded structural rehabilitation/surface rehabilitation affecting rutting progression within progression year ranges were also discarded.
8. For the selected segments, rut progression was calculated within the selected start and end year ranges.

The flowchart showing the segment selection process is presented in Figure 2.2 and the ratio between initial segments and selected segments (for each region) is presented in Table 2.1. All regions except the Kimberley had data coverage of around 80%. For the Kimberley, 66% of the total sub-network length was analysed and this might skew the rutting progression trend observed for this region.

Figure 2.2: Segment selection steps for rut progression calculation

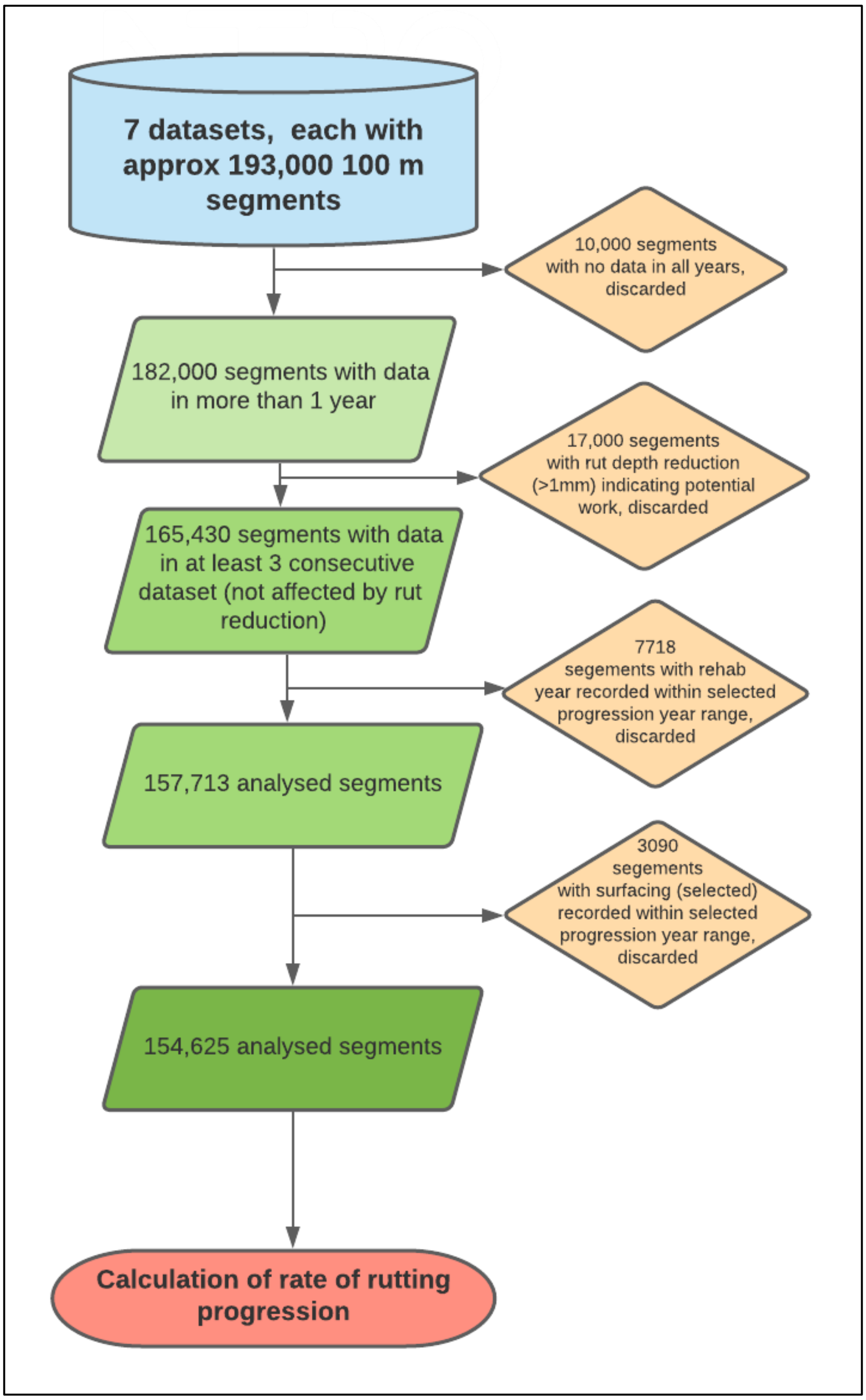


Table 2.1: Comparison of supplied length and selected analysis length for MRWA regions

Region	Length from supplied data (km)	Analysed length (km)	% Length
Great Southern	1,632	1,354.55	83
South-West	1,861.66	1,591.75	86
Goldfields-Esperance	2,489.31	2,097.96	84
Kimberley	2,133.09	1,417.88	66
Metro	1,386.52	863.12	62
Wheatbelt	3,022.18	2,574.43	85
Pilbara	2,989.26	2,324.8	78
Mid-West Gascoyne	3,727.07	3,212.32	86

2.3.2 Effect of MMIS on Rut Progression

The segment selection process outlined in Section 2.3.1 should have eliminated the effect of any maintenance. While the actual amount of the routine maintenance cost was not available, the MMIS defect information (defects translated in $ term, see Table 2.2) gives some indication of the extent of the defects reported for each region.

Table 2.2: Historical MMIS defect intensity for different regions

Region	MMIS_Cost1516	MMIS_Cost1617	MMIS_Cost1718	MMIS_Cost1819	MMIS_Cost1920	MMIS_Cost2021
Great Southern	$5,145,707	$5,504,878	$5,758,257	$2,132,252	$5,551,592	$2,984,828
South-West	$2,099,508	$2,124,732	$1,644,106	$1,790,934	$3,564,875	$2,319,363
Goldfields-Esperance	$6,524,519	$12,795,837	$14,815,436	$26,875,516	$9,575,659	$6,776,209
Kimberley	$4,540,703	$2,272,001	$595,749	$899,541	$4,775,013	$2,554,044
Metro	$219,844	$482,924	$453,156	$242,663	$285,700	$578,989
Wheatbelt	$9,782,664	$4,769,277	$2,806,196	$6,674,146	$5,198,119	$19,867,277
Pilbara	$3,168,485	$2,075,215	$9,395,939	$6,371,440	$5,858,517	$6,490,763
Mid-West Gascoyne	$8,625,008	$6,164,940	$16,416,238	$11,612,380	$10,123,986	$12,104,129

As shown in the Table, the Goldfields-Esperance and Mid-West Gascoyne regions had more defects reported in different years and the Metro and Kimberley regions had significantly less defects reported in different years. These reported defects (including the level of accuracy in reporting) and any routine maintenance used to rectify those defects might affect the rate of rutting progression estimated for the regions.

2.4 Rut Progression Analysis and Performance Matrix Development

2.4.1 Rut Progression Ranges

Rut progression values calculated for the analysed segments were grouped into the following 7 bands:

- < 0 (some segments show negative trend. However, the fluctuation over time was not huge enough to flag a possible maintenance intervention)
- 0−0.1 mm/year
- 0.1−0.25 mm/year
- 0.25−0.5 mm/year
- 0.5−0.75 mm/year
- 0.75−1 mm/year
- >1 mm/year.

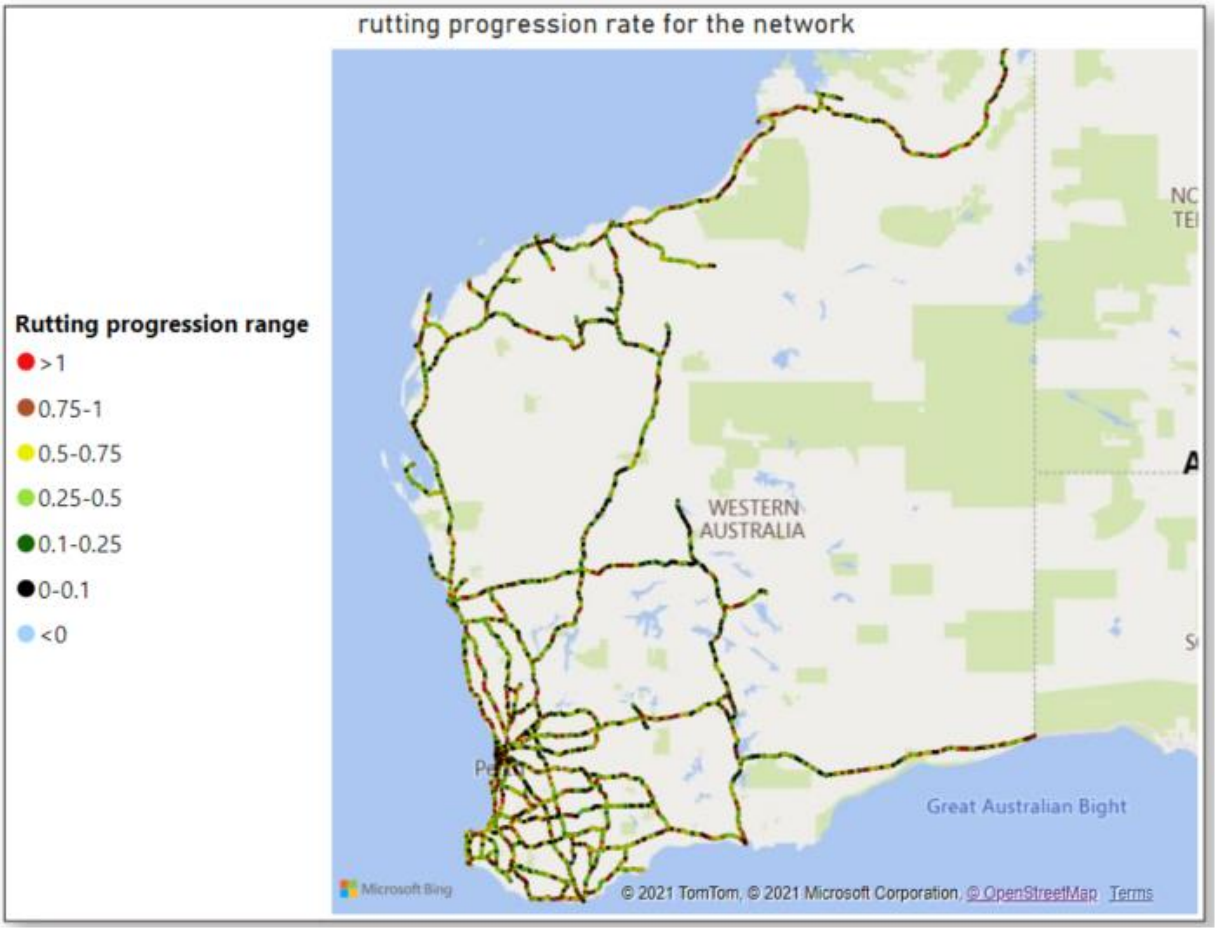
Rut progression in terms of these bands for the whole network is presented in Table 2.3 and Figure 2.3.

Table 2.3: Per cent segment in different rutting bands

Band	Length (km)	% network length
<0	578.38	3.7%
0−0.1	1,007.98	6.5%
0.1−0.25	2,985.33	19.3%
0.25−0.5	4,774.51	30.9%
0.5−0.75	2,544.3	16.5%
0.75−1	1,436.57	9.3%

Band	Length (km)	% network length
> 1	2,110.94	13.7%

Figure 2.3: Rutting progression rate across the network



As Table 2.3 shows, 30% of the network has a rutting progression rate between 0.25−0.5 mm/ year. There is also a substantial portion (13.7%) of the network with more than 1 mm/year rutting progression.

2.4.2 Independent Variable for Matrix Development

The following independent parameters were used in developing different performance matrices to show the average rutting progression as well as the % length of the network sitting in various rutting progression rate bands. Since the data collection spanned from 2007 to 2020, for annualised variables such as AADT, pavement age, surface age, etc. mid-range values (2014 values) were used.

- WA Regions
- Cluster IDs
- AADT range (2014 values)
- Pavement age and surface age range (2014 values)
- Annual rainfall
- Link category
- Thornthwaite Moisture Index (TMI).

2.5 Output from Different Performance Matrices

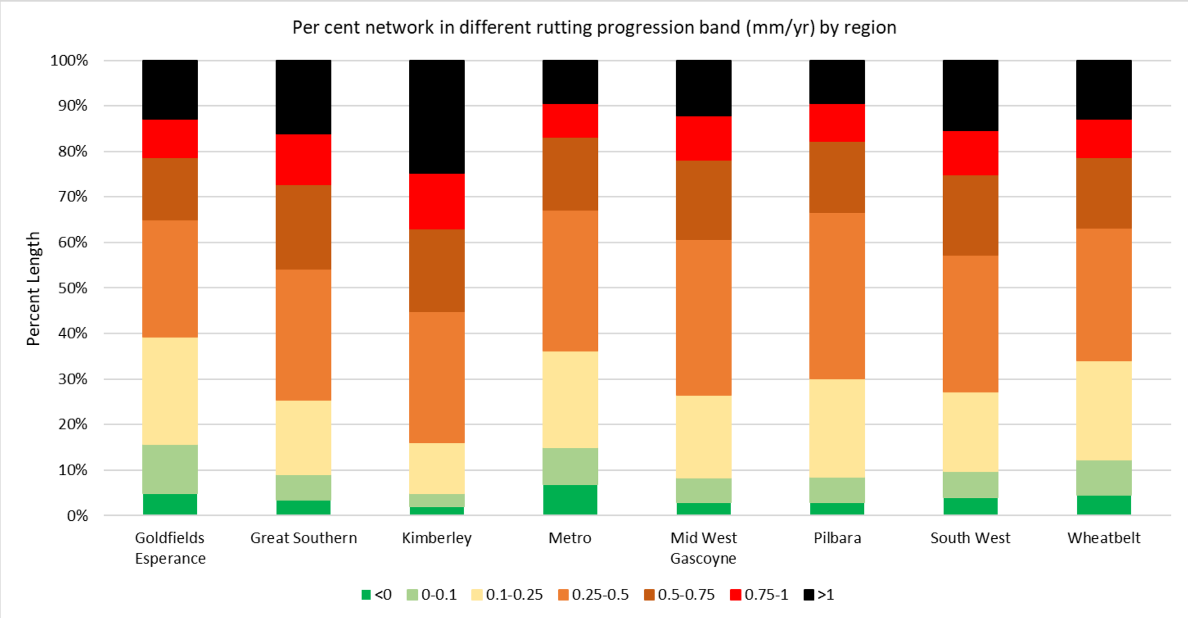
2.5.1 Rut Progression Across Regions

Table 2.4 summarises the average rutting progression for each WA region and Figure 2.4 displays the % length in different rutting progression bands for each region.

Table 2.4: Average rut progression for the regions

Region name	Average rutting progression (mm/year)
Great Southern	0.59
South-West	0.57
Goldfields-Esperance	0.49
Kimberley	0.69
Metro	0.45
Wheatbelt	0.52
Pilbara	0.47
Mid-West Gascoyne	0.52

Figure 2.4: Per cent length in different rut progression ranges for the regions



The average rut progression values ranged from 0.4 to 0.7 mm/year for all regions with the Kimberley displaying the highest average rutting progression (0.69 mm/year) followed by Great Southern (0.59 mm/year) (see Table 2.4). In terms of rutting progression across different bands (see Figure 2.4), almost one-third of the length in each region has rut progression between 0.25 to 0.5 mm/year. Similar to the network level average, nearly 10% of the length in each region has rut progression of more than 1 mm/year. The Kimberley has the highest proportion of the network in the highest band, around 25% length, followed by Great Southern and South-West.

The regional distributions of rutting progressions are plotted in Figure 2.5, with 50th percentile (median values) summarised in Table 2.5. Distributions are similar across the regions. The Kimberley had the highest 50th percentile rutting progression rate (0.56 mm/year) and Metro and Goldfields-Esperance had the lowest median rut progression rates (0.34 mm/year and 0.33 mm/year).

Figure 2.5: Rutting progression distribution by region

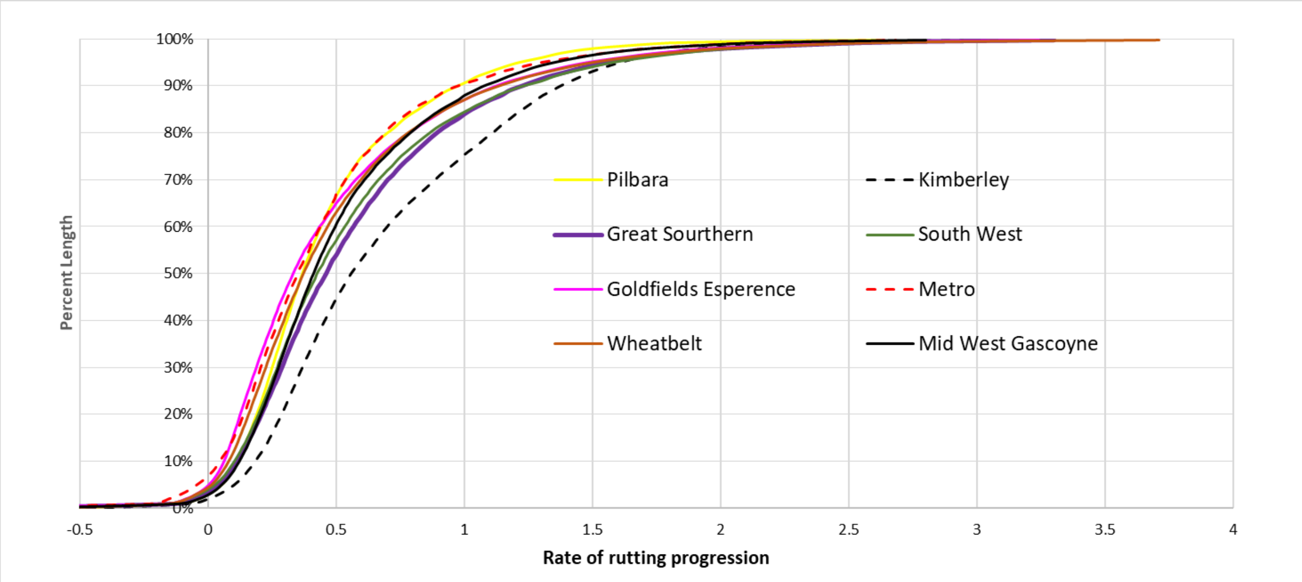


Table 2.5: 50th percentile rut progression rate by region

Region name	50th percentile values (mm/year)
Kimberley	0.56
Great Southern	0.460
South-West	0.43
Mid-West Gascoyne	0.41
Wheatbelt	0.37
Pilbara	0.37
Metro	0.34
Goldfields-Esperance	0.33

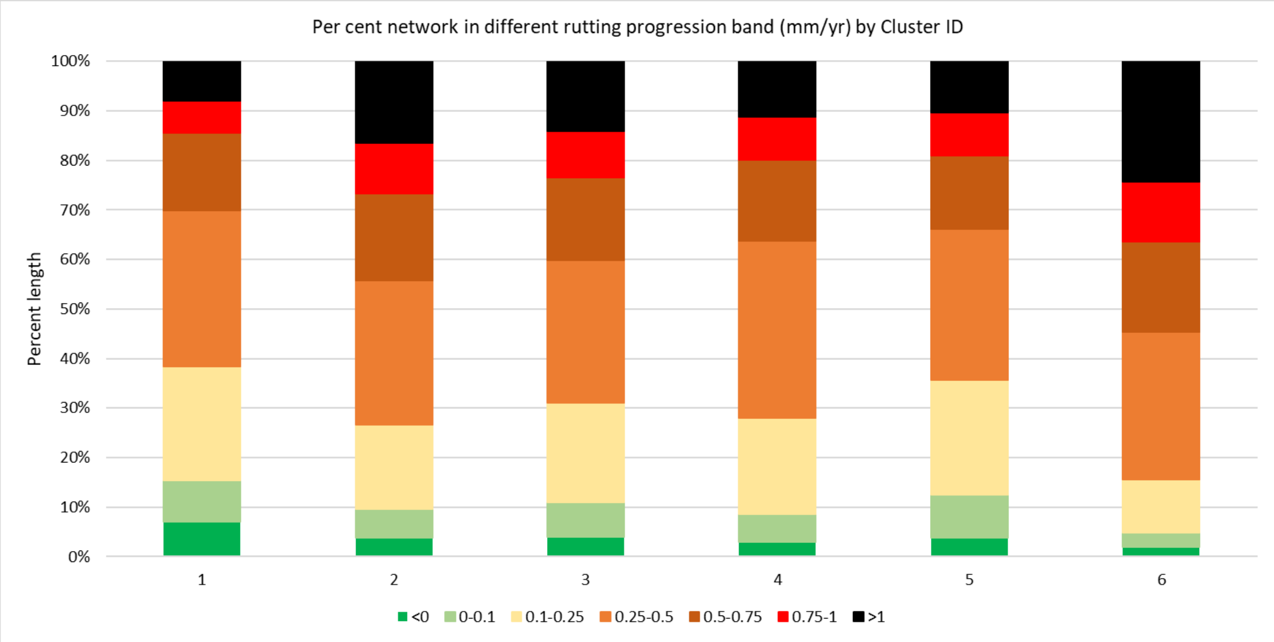
2.5.2 Rut Progression Across Cluster ID

Rutting progression rates were checked against MRWA Cluster data IDs as identified, supplied, and requested by MRWA. Table 2.6 summarises the average rutting progression for each WA Cluster and Figure 2.6 displays the % length in different rutting progression band for all Clusters.

Table 2.6: Average rut progression for the Cluster IDs

Cluster ID	Average rutting progression (mm/year)
1	0.42
2	0.59
3	0.54
4	0.50
5	0.47
6	0.69

Figure 2.6: Per cent length in different rut progression band for Cluster IDs



Similar rutting progression observations as those in the regions hold true for Cluster IDs as MRWA clusters are geographically distributed.

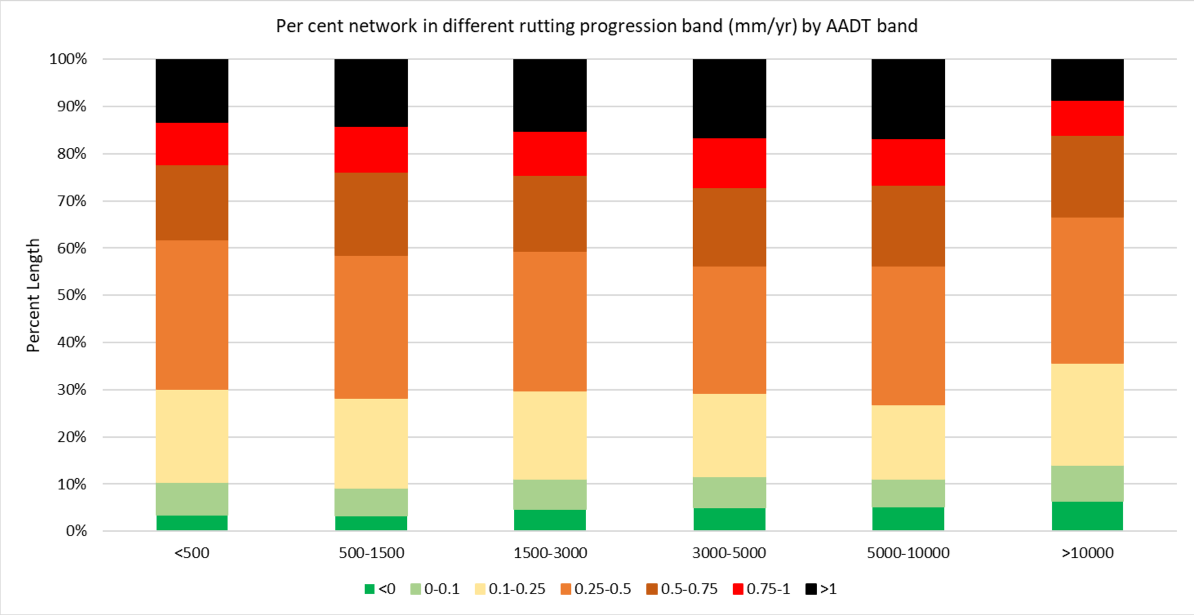
2.5.3 Rut Progression Across Various Traffic Ranges

Traffic (AADT) values from 2014 were used for the performance matrix development. The AADT was grouped into 6 bands. Table 2.7 summarises the average rutting progression for the AADT bands and Figure 2.7 displays the % length in different rutting progression ranges for the AADT bands.

Table 2.7: Average rut progression for the various traffic bands

AADT	Average rutting progression (mm/year)
< 500	0.52
500–1,500	0.55
1,500–3,000	0.56
3,000–5,000	0.58
5,000–10,000	0.58
> 10,000	0.44

Figure 2.7: Per cent length in different rut progression band for traffic bands



In general, higher AADT is associated with lower average rut progression as pavements carrying higher traffic are usually designed to higher standards. Almost 30% of the length in each AADT band has rutting progression at 0.25 to 0.5 mm/year. However, with an increase in AADT, a higher % length in the lower rutting progression rate band is observed and vice versa. This is also expected and aligns with the pavement design standards.

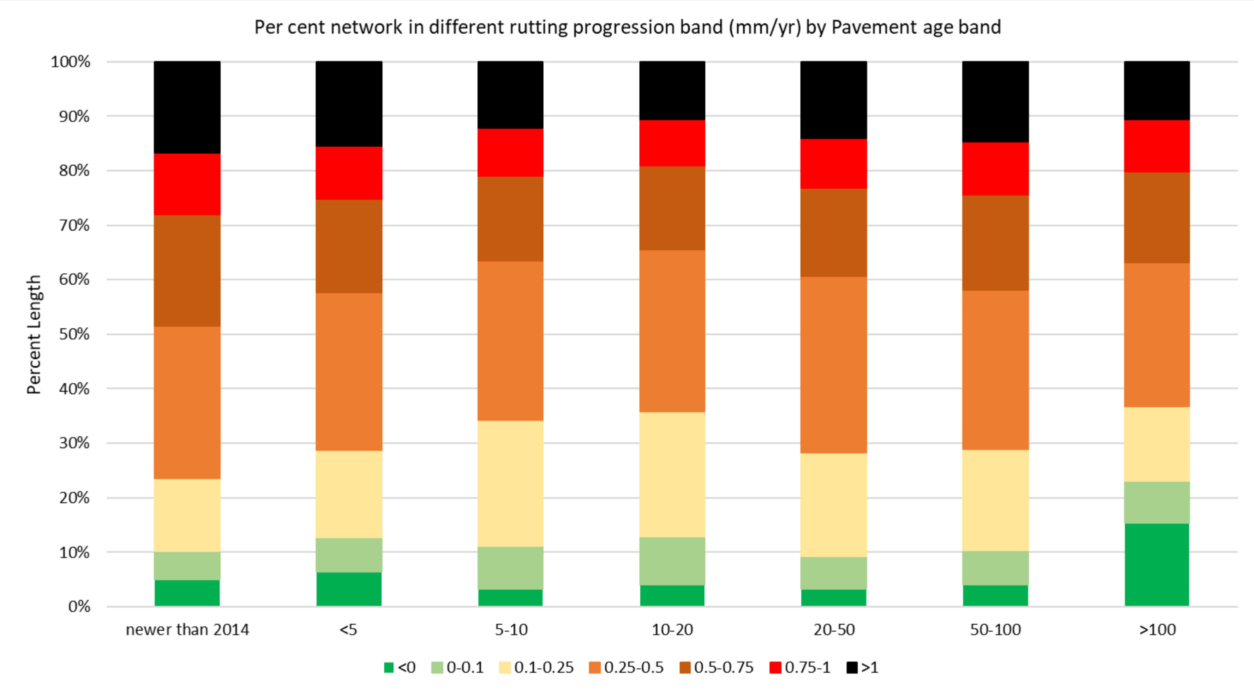
2.5.4 Rut Progression for Pavement Age and Traffic Combinations

Similar to the traffic, pavement age values from 2014 were used for the performance matrix development. Pavement ages were grouped into 7 bands with a separate category where the age was more recent than 2014. Table 2.8 summarises the average rutting progression by pavement age band and Figure 2.8 displays the % length in different rutting progression bands for pavement age bands.

Table 2.8: Average rut progression for the various pavement age bands

Pavement age	Average rutting progression (mm/year)
Newer than 2014	0.62
< 5	0.56
5–10	0.51
10–20	0.47
20–50	0.53
50–100	0.55
> 100	0.44

Figure 2.8: Per cent length in different rut progression band for pavement age bands



The average rutting progression values are similar across pavement age bands. However, pavements newer than 2014 show higher average rut progression and relatively old pavements show reduced rut progression (‘survivor’ effect for old and strong pavements). It should be noted that, segments with a pavement age greater than 100 years constitute less than 0.5% of the network length.

The percentage length in different rut progression bands for pavement age and traffic combinations for the Metro and Kimberley regions were also checked and the results are presented in Table 2.9 and Table 2.10 respectively. For Metro, on average, rutting progression mostly sits within 0.25 to 0.5 mm/year across all AADT and age bands. Higher AADT bands are associated with more lengths in the lower rutting progression bands across all age groups.

Table 2.9: Per cent length in different rut progression band for pavement age and traffic combinations for Metro region

AADT_Range	Pavement age range	Rutting progression (mm/year)						
		< 0	00.1	0.1–0.25	0.25–0.5	0.5–0.75	0.75–1	> 1
< 500	5–10	7.69%	0.00%	0.00%	38.46%	30.77%	7.69%	15.38%
	10–20	15.38%	0.00%	7.69%	23.08%	30.77%	15.38%	7.69%
	20–50	44.44%	0.00%	11.11%	22.22%	0.00%	0.00%	22.22%
	> 100	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%
500–1,500	5–10	0.00%	0.00%	4.35%	21.74%	56.52%	13.04%	4.35%
	10–20	0.00%	0.00%	25.00%	50.00%	0.00%	12.50%	12.50%
1,500–3,000	Newer than 2014	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%
	5–10	0.00%	6.25%	6.25%	43.75%	31.25%	6.25%	6.25%
	10–20	5.73%	7.49%	20.26%	30.40%	10.13%	6.17%	19.82%
	20–50	5.91%	6.72%	17.47%	25.00%	19.62%	10.22%	15.05%
	50–100	6.52%	5.43%	16.30%	34.78%	10.87%	8.70%	17.39%
3,000–5,000	< 5	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	5–10	2.29%	3.82%	23.66%	34.35%	19.85%	9.16%	6.87%
	10–20	6.67%	5.00%	16.67%	27.50%	17.50%	12.50%	14.17%
	20–50	9.52%	2.38%	11.90%	35.71%	23.81%	11.90%	4.76%
	50–100	4.55%	8.33%	22.73%	24.24%	17.42%	8.33%	14.39%

AADT_Range	Pavement age range	Rutting progression (mm/year)						
		< 0	00.1	0.1–0.25	0.25–0.5	0.5–0.75	0.75–1	> 1
5,000–10,000	Newer than 2014	25.00%	0.00%	0.00%	50.00%	12.50%	12.50%	0.00%
	< 5	0.00%	0.00%	12.00%	44.00%	12.00%	20.00%	12.00%
	5–10	2.67%	2.14%	13.37%	34.76%	23.53%	5.35%	18.18%
	10–20	7.25%	13.33%	17.10%	25.80%	13.33%	8.41%	14.78%
	20–50	9.00%	8.56%	18.55%	29.31%	13.50%	8.56%	12.51%
	50–100	6.58%	8.33%	21.49%	34.21%	15.35%	7.46%	6.58%
	> 100	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
> 10,000	Newer than 2014	5.88%	1.96%	15.69%	35.29%	35.29%	3.92%	1.96%
	< 5	0.61%	2.45%	10.43%	32.52%	26.38%	9.20%	18.40%
	5–10	2.66%	5.32%	16.61%	33.89%	19.93%	11.63%	9.97%
	10–20	7.86%	8.52%	21.76%	29.88%	18.09%	6.68%	7.21%
	20–50	6.29%	9.10%	25.24%	31.81%	14.37%	5.74%	7.45%
	50–100	4.26%	7.17%	26.16%	35.47%	16.86%	6.01%	4.07%
	> 100	18.36%	7.97%	13.77%	25.12%	15.94%	11.59%	7.25%

For the Kimberley, a significant length also displays a rate of rutting > 1 mm/ year for the lower AADT roads. Higher AADT bands are associated with more lengths in lower rutting progression ranges across all age groups.

Table 2.10: Per cent length in different rut progression band for pavement age and traffic combinations for Kimberley region

AADT range	Pavement age range	Rutting progression (mm/year)						
		< 0	0–0.1	0.1–0.25	0.25–0.5	0.5–0.75	0.75–1	> 1
< 500	Newer than 2014	2.28%	3.33%	12.08%	28.55%	20.67%	13.13%	19.96%
	< 5	3.35%	5.03%	8.94%	21.23%	12.85%	12.85%	35.75%
	5–10	1.36%	1.09%	6.79%	29.89%	24.46%	14.13%	22.28%
	10–20	2.17%	3.53%	11.52%	32.31%	25.32%	10.28%	14.86%
	20–50	1.49%	2.73%	11.34%	29.53%	16.83%	11.91%	26.15%
	50–100	2.07%	1.38%	8.97%	29.66%	20.69%	18.62%	18.62%
	> 100	0.00%	0.00%	50.00%	0.00%	0.00%	50.00%	0.00%
500–1,500	Newer than 2014	1.27%	1.27%	1.91%	8.92%	9.55%	21.02%	56.05%
	5–10	0.00%	0.76%	6.82%	16.67%	25.00%	23.48%	27.27%
	10–20	1.77%	1.33%	5.75%	37.17%	26.99%	12.39%	14.60%
	20–50	2.33%	3.84%	11.48%	25.01%	17.16%	12.24%	27.94%
	50–100	12.00%	4.00%	20.00%	24.00%	8.00%	4.00%	28.00%
	> 100	0.00%	9.09%	0.00%	27.27%	36.36%	18.18%	9.09%
1,500–3,000	5–10	42.86%	10.20%	4.08%	14.29%	10.20%	10.20%	8.16%
	10–20	31.25%	9.38%	25.00%	21.88%	9.38%	3.13%	0.00%
	20–50	5.48%	5.48%	6.85%	16.44%	19.18%	8.22%	38.36%
	50–100	50.00%	50.00%	0.00%	0.00%	0.00%	0.00%	0.00%
3,000–5,000	20–50	8.33%	4.17%	20.83%	29.17%	8.33%	20.83%	8.33%
5,000–10,000	5–10	40.00%	0.00%	30.00%	20.00%	0.00%	10.00%	0.00%

2.5.5 Rut Progression by Surface Age

For the current analysis, the preventative maintenance indicator (PMI) was used as a surrogate of surface age with respect to binder life. The PMI is calculated as the ratio between surface age and predicted seal life and reported as a 5-scale classification (Table 2.11). Seal life as used in Table 2.12 was based on MRWA region as per MRWA's modelling document (MRWA 2019). Since 95% of the analysed segments have sprayed seal surfacing, for simplification, maximum sprayed seal life was used only, and maximum asphalt life was not considered.

Table 2.11: PMI classification

Surface age/seal life	PMI
0	Very Good
0.5	Good
1	Mediocre
1.3	Poor
1.6	Very Poor

Table 2.12: Maximum seal life by WA region

Region	Seal life
Metro	20
Great Southern	18
South-West	17
Goldfields-Esperance	16
Kimberley	15
Wheatbelt	18
Pilbara	15
Mid-West Gascoyne	15

The percentage network length in different rut progression bands for PMI ranges for regions is outlined in Table 2.13.

Table 2.13: Per cent length in different rut progression band for PMI range for each region

Region name	PMI range	Rutting progression (mm/year)						
		< 0	0–0.1	0.1–0.25	0.25–0.5	0.5–0.75	0.75–1	> 1
Goldfields Esperance	Very Good	4.95%	8.81%	21.64%	26.85%	14.79%	9.02%	13.95%
	Good	5.41%	16.95%	26.79%	21.47%	10.95%	7.18%	11.26%
	Mediocre	2.88%	19.23%	38.68%	22.93%	7.77%	3.92%	4.59%
	Poor	3.10%	17.83%	31.78%	17.05%	14.73%	7.75%	7.75%
	Very Poor	5.80%	7.25%	27.54%	23.19%	14.49%	7.25%	14.49%
Great Southern	Very Good	3.57%	5.52%	16.28%	28.81%	18.48%	11.23%	16.11%
	Good	3.07%	5.51%	16.10%	28.07%	20.02%	10.49%	16.74%
	Mediocre	4.08%	7.43%	23.02%	30.70%	17.27%	8.87%	8.63%
	Poor	2.17%	4.88%	15.18%	29.81%	23.31%	11.65%	13.01%
	Very Poor	1.71%	3.90%	15.85%	24.88%	19.27%	11.46%	22.93%
Kimberley	Very Good	2.28%	3.17%	11.41%	28.51%	20.19%	12.52%	21.93%
	Good	1.51%	2.61%	9.39%	28.31%	13.79%	10.87%	33.51%
	Mediocre	0.82%	1.98%	12.70%	34.62%	11.19%	12.00%	26.69%
	Poor	0.00%	2.70%	5.41%	13.51%	27.03%	5.41%	45.95%
	Very Poor	1.95%	2.93%	9.27%	25.37%	19.02%	12.20%	29.27%
Metro	Very Good	6.43%	8.10%	20.83%	30.29%	17.54%	7.56%	9.25%
	Good	4.30%	7.63%	23.80%	36.99%	13.05%	5.69%	8.54%
	Mediocre	8.51%	7.57%	23.75%	25.92%	13.15%	7.76%	13.34%
	Poor	3.30%	11.88%	26.07%	34.98%	15.18%	4.62%	3.96%

Region name	PMI range	Rutting progression (mm/year)						
		< 0	0–0.1	0.1–0.25	0.25–0.5	0.5–0.75	0.75–1	> 1
	Very Poor	11.43%	7.93%	17.24%	29.22%	15.94%	8.94%	9.31%
Mid West Gascoyne	Very Good	3.02%	5.48%	18.85%	34.18%	17.25%	9.22%	12.01%
	Good	2.26%	5.15%	17.83%	34.12%	16.33%	12.15%	12.17%
	Mediocre	3.57%	4.19%	11.76%	33.74%	25.62%	8.19%	12.93%
	Poor	1.05%	4.88%	15.68%	32.40%	15.68%	13.24%	17.07%
	Very Poor	6.25%	5.00%	17.50%	28.75%	13.75%	5.63%	23.13%
Pilbara	Very Good	3.06%	5.54%	20.39%	37.05%	16.00%	8.28%	9.68%
	Good	2.67%	4.86%	21.59%	36.15%	15.07%	9.39%	10.28%
	Mediocre	2.08%	9.67%	37.61%	30.83%	11.48%	4.61%	3.71%
	Very Poor	3.70%	13.58%	25.93%	30.86%	18.52%	2.47%	4.94%
South West	Very Good	4.32%	5.75%	15.85%	29.52%	18.44%	10.24%	15.88%
	Good	4.15%	5.65%	20.74%	31.31%	15.22%	7.98%	14.95%
	Mediocre	1.96%	6.63%	24.34%	30.80%	15.05%	7.84%	13.38%
	Poor	3.28%	3.83%	15.30%	31.33%	18.76%	11.66%	15.85%
	Very Poor	4.02%	5.36%	21.43%	29.46%	17.41%	8.48%	13.84%
Wheatbelt	Very Good	4.54%	7.66%	21.88%	29.70%	15.34%	8.34%	12.54%
	Good	4.10%	8.52%	22.59%	27.13%	15.34%	8.09%	14.22%
	Mediocre	4.57%	9.15%	20.91%	26.56%	15.67%	9.55%	13.58%
	Poor	4.64%	6.70%	19.59%	27.84%	19.07%	9.54%	12.63%
	Very Poor	5.17%	5.17%	17.29%	31.19%	17.47%	8.56%	15.15%

A 'Very Poor' PMI was found to be associated with an increased length in the higher rut progression band (> 1 mm) for the Great Southern, Kimberley and Mid-West Gascoyne regions.

2.5.6 Rut Progression for Traffic and TMI Combinations

TMI values were calculated for each 100 m segment using the Climate Tool (Austroads 2010a). Lower TMI values (including negatives) indicate a drier condition and higher TMI values indicate wetter conditions. The calculated TMI values were grouped into 6 bands. The percentage length in different rut progression bands for TMI and traffic combinations are presented in Table 2.14.

Table 2.14: Per cent length in different rut progression band for TMI and traffic combinations

AADT range	TMI range	Rutting progression (mm/year)						
		< 0	0–0.1	0.1–0.25	0.25–0.5	0.5–0.75	0.75–1	> 1
< 500	(−100)−(−40)	3.79%	7.91%	23.84%	46.15%	8.99%	4.33%	4.98%
	−40−0	3.37%	7.02%	19.95%	31.71%	15.63%	9.18%	13.13%
	0−10	2.51%	3.70%	12.40%	31.01%	20.81%	12.24%	17.33%
	10−20	3.01%	5.61%	13.33%	27.97%	20.16%	9.43%	20.49%
	20−40	3.08%	7.49%	22.46%	32.61%	15.68%	7.14%	11.55%
	40−80	3.35%	6.24%	21.60%	32.43%	14.77%	8.11%	13.52%
500–1,500	(−100)−(−40)	3.47%	8.15%	22.87%	33.76%	14.90%	8.03%	8.82%
	−40−0	3.36%	5.67%	19.56%	30.41%	17.32%	9.57%	14.11%
	0−10	2.40%	4.54%	11.48%	23.63%	22.70%	12.28%	22.96%
	10−20	1.68%	3.64%	10.31%	25.27%	21.85%	13.84%	23.42%
	20−40	3.74%	6.17%	16.80%	31.87%	17.85%	9.48%	14.08%
	40−80	2.89%	5.34%	19.42%	30.36%	19.67%	9.49%	12.82%

AADT range	TMI range	Rutting progression (mm/year)						
		< 0	0–0.1	0.1–0.25	0.25–0.5	0.5–0.75	0.75–1	> 1
1,500–3,000	−40–0	4.32%	6.52%	18.86%	30.37%	16.52%	9.38%	14.02%
	0–10	3.45%	6.31%	19.17%	32.38%	16.90%	9.05%	12.74%
	10–20	4.31%	4.31%	13.54%	27.69%	16.62%	11.08%	22.46%
	20–40	5.01%	5.37%	18.62%	27.53%	15.26%	9.89%	18.32%
	40–80	4.10%	5.62%	13.47%	26.23%	16.98%	10.30%	23.30%
3,000–5,000	−40–0	6.43%	7.36%	20.05%	27.24%	15.37%	10.11%	13.44%
	0–10	2.22%	6.35%	17.14%	20.00%	20.00%	9.52%	24.76%
	10–20	4.57%	6.33%	19.33%	27.07%	15.82%	9.67%	17.22%
	20–40	3.63%	4.84%	12.74%	24.65%	20.00%	13.21%	20.93%
	40–80	5.55%	5.39%	18.38%	30.90%	13.63%	10.30%	15.85%
5,000–10,000	−40–0	7.63%	5.57%	18.76%	28.35%	14.33%	8.04%	17.32%
	0–10	3.59%	8.55%	18.46%	30.43%	16.75%	9.23%	12.99%
	10–20	12.01%	10.25%	16.61%	31.45%	10.25%	8.13%	11.31%
	20–40	3.12%	5.16%	13.64%	26.87%	19.20%	10.92%	21.10%
	40–80	4.03%	4.34%	14.90%	29.09%	19.32%	11.64%	16.68%
> 10,000	−40–0	6.03%	5.32%	20.45%	32.41%	16.87%	7.57%	11.35%
	0–10	6.27%	9.82%	25.15%	30.10%	15.93%	7.31%	5.43%
	10–20	3.70%	5.56%	21.81%	35.19%	19.14%	6.58%	8.02%
	20–40	4.79%	6.02%	17.82%	32.67%	17.82%	8.25%	12.62%
	40–80	4.27%	7.01%	15.73%	26.15%	20.85%	10.94%	15.04%

For all traffic bands, a wetter TMI is associated with a larger percentage length in higher rutting progression bands. This observation also holds true at a regional level (see Table 2.15) except for Metro and Pilbara (not included in the table). It should be noted the Pilbara has a very low TMI, representing an arid or semi-arid climate, with all segments sitting within the range −40 to 0 TMI.

Table 2.15: Per cent length in different rut progression band for TMI and traffic combinations-selected regions

Region	AADT range	TMI range	Rutting progression (mm/year)						
			<0	0-0.1	0.1-0.25	0.25-0.5	0.5-0.75	0.75-1	>1
Goldfields Esperance	< 500	−40–0	4.56%	11.79%	25.76%	26.15%	12.52%	7.85%	11.38%
	500–1,500	−40–0	4.84%	7.10%	17.65%	25.15%	17.36%	10.21%	17.69%
		0–10	4.03%	4.70%	12.08%	21.81%	20.13%	10.74%	26.51%
	1,500–3,000	−40–0	3.24%	11.60%	21.70%	24.56%	15.46%	8.73%	14.71%
		0–10	2.13%	8.51%	17.02%	19.15%	25.53%	8.51%	19.15%
	3,000–5,000	−40–0	27.59%	10.34%	34.48%	12.07%	8.62%	1.72%	5.17%
		0–10	0.00%	0.00%	14.29%	25.71%	31.43%	14.29%	14.29%
	5,000–10,000	−40–0	15.56%	17.78%	33.33%	22.22%	2.22%	2.22%	6.67%
Kimberley	< 500	−40–0	1.50%	2.80%	11.19%	29.42%	17.06%	11.74%	26.29%
		0–10	2.07%	2.62%	11.33%	31.92%	21.99%	13.07%	17.00%
		10–20	2.56%	4.33%	10.63%	24.41%	24.41%	10.04%	23.62%
	500–1,500	−40–0	2.30%	2.74%	9.85%	22.37%	16.22%	13.70%	32.81%
		10–20	1.73%	2.23%	5.94%	26.36%	21.66%	14.60%	27.48%
	1,500–3,000	−40–0	37.08%	12.36%	11.24%	16.85%	11.24%	5.62%	5.62%
	3,000–5,000	10–20	8.33%	4.17%	20.83%	29.17%	8.33%	20.83%	8.33%
	5,000–10,000	−40–0	33.33%	0.00%	33.33%	22.22%	0.00%	11.11%	0.00%
South West	< 500	0–10	5.58%	3.59%	15.14%	23.90%	19.52%	10.36%	21.91%

Region	AADT range	TMI range	Rutting progression (mm/year)						
			<0	0-0.1	0.1-0.25	0.25-0.5	0.5-0.75	0.75-1	>1
		10–20	6.23%	10.51%	19.46%	33.07%	18.68%	5.84%	6.23%
		20–40	3.58%	8.83%	23.08%	29.98%	15.21%	6.91%	12.41%
		40–80	3.46%	6.38%	21.77%	32.08%	14.58%	8.07%	13.67%
	500–1,500	−40–0	2.40%	5.39%	10.18%	30.54%	21.56%	18.56%	11.38%
		0–10	0.00%	3.23%	16.13%	24.19%	29.03%	12.90%	14.52%
		10–20	1.19%	1.19%	7.14%	23.81%	20.24%	16.67%	29.76%
		20–40	3.94%	6.07%	17.05%	32.93%	18.27%	8.59%	13.15%
		40–80	3.67%	5.88%	20.12%	29.58%	19.18%	9.21%	12.36%
	1,500–3,000	−40–0	0.00%	0.00%	33.33%	16.67%	16.67%	16.67%	16.67%
		20–40	5.36%	5.43%	19.37%	27.20%	15.52%	9.82%	17.31%
		40–80	3.34%	5.52%	11.92%	25.00%	17.88%	11.63%	24.71%
	3,000–5,000	20–40	3.05%	4.58%	11.69%	25.59%	20.51%	15.08%	19.49%
		40–80	5.55%	5.39%	18.38%	30.90%	13.63%	10.30%	15.85%
	5,000–10,000	20–40	2.52%	4.14%	12.50%	26.79%	19.81%	11.36%	22.89%
		40–80	3.88%	4.45%	14.96%	29.43%	19.00%	11.56%	16.73%
	> 10,000	20–40	2.62%	2.13%	10.80%	27.82%	24.88%	13.09%	18.66%
		40–80	1.61%	3.21%	9.24%	26.10%	27.71%	15.66%	16.47%

2.5.7 Rut Progression for Traffic and Rainfall Combinations

The annual rainfall data supplied by MRWA was grouped into 4 bands. The percentage length in each different rut progression band for rainfall and traffic combinations for selected regions are presented in Table 2.16.

Table 2.16: Per cent length in different rut progression band for rainfall and traffic combinations-selected regions

Region	AADT range	Rainfall range	Rutting progression (mm/year)						
			< 0	0–0.1	0.1–0.25	0.25–0.5	0.5–0.75	0.75–1	> 1
Great Southern	< 500	200–500	3.97%	5.72%	16.33%	27.91%	18.95%	11.68%	15.45%
		500–800	2.32%	5.97%	19.66%	31.74%	15.10%	9.62%	15.59%
		800–1,200	0.00%	2.04%	16.33%	42.86%	20.41%	9.18%	9.18%
	500–1,500	200–500	5.51%	6.52%	18.61%	30.32%	19.24%	8.99%	10.82%
		500–800	2.39%	5.38%	14.05%	23.77%	21.67%	12.86%	19.88%
		800–1,200	1.65%	4.35%	14.84%	28.07%	20.78%	13.14%	17.18%
	1,500–3,000	200–500	3.48%	3.48%	12.17%	33.48%	22.17%	8.70%	16.52%
		500–800	4.30%	6.02%	16.73%	30.40%	17.50%	9.94%	15.11%
		800–1,200	2.44%	2.93%	12.93%	30.49%	15.12%	11.22%	24.88%
		500–800	4.78%	8.76%	19.52%	33.47%	9.96%	6.77%	16.73%
	3,000–5,000	800–1,200	3.00%	4.39%	12.93%	20.55%	20.09%	12.24%	26.79%
	5,000–10,000	800–1,200	0.00%	4.55%	18.18%	19.70%	21.21%	12.12%	24.24%
	> 10,000	800–1,200	0.00%	14.29%	21.43%	42.86%	21.43%	0.00%	0.00%
Metro	< 500	500–800	37.50%	0.00%	0.00%	0.00%	12.50%	12.50%	37.50%
		800–1,200	14.29%	3.57%	7.14%	35.71%	25.00%	7.14%	7.14%
	500–1,500	800–1,200	0.00%	0.00%	9.68%	29.03%	41.94%	12.90%	6.45%
	1,500–3,000	200–500	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%
		500–800	10.81%	8.11%	5.41%	14.86%	20.27%	16.22%	24.32%

Region	AADT range	Rainfall range	Rutting progression (mm/year)						
			< 0	0–0.1	0.1–0.25	0.25–0.5	0.5–0.75	0.75–1	> 1
		800–1,200	5.21%	6.64%	19.27%	30.02%	15.17%	7.90%	15.80%
	3,000–5,000	500–800	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%
		800–1,200	5.18%	5.41%	20.24%	29.41%	18.82%	9.88%	11.06%
	5,000–10,000	500–800	8.20%	9.18%	17.87%	24.75%	11.97%	10.82%	17.21%
		800–1,200	7.31%	8.31%	17.90%	33.15%	16.35%	6.76%	10.23%
	> 10,000	500–800	11.24%	9.71%	23.43%	24.67%	14.19%	7.14%	9.62%
		800–1,200	5.85%	8.03%	23.04%	33.08%	16.39%	6.59%	7.02%
South West	< 500	500–800	5.97%	8.21%	20.15%	27.36%	17.29%	7.34%	13.68%
		800–1,200	3.28%	6.82%	21.93%	31.98%	14.82%	7.87%	13.30%
	500–1,500	500–800	3.52%	4.56%	11.99%	26.86%	23.08%	13.82%	16.17%
		800–1,200	4.10%	6.35%	18.77%	32.68%	17.73%	8.23%	12.15%
	1,500–3,000	500–800	0.00%	0.00%	33.33%	16.67%	16.67%	16.67%	16.67%
		800–1,200	4.83%	5.65%	17.43%	26.32%	16.48%	10.27%	19.03%
	3,000–5,000	800–1,200	4.38%	4.94%	15.21%	28.50%	17.20%	12.42%	17.36%
	5,000–10,000	800–1,200	3.48%	4.36%	13.46%	30.22%	18.78%	10.93%	18.78%
	> 10,000	800–1,200	4.22%	3.92%	12.75%	27.75%	24.02%	11.86%	15.49%

The annual rainfall range does not add any additional explanation to the rutting progression rates for the regions. The percentage lengths in different rut progression bands are similar across various rainfall ranges. For rainfall ranges 800 to 1,200 mm, the Great Southern and South-West regions display a slightly increased % length in the highest rutting progression band (> 1 mm). However, this observation is not consistent with other regions (e.g., Metro).

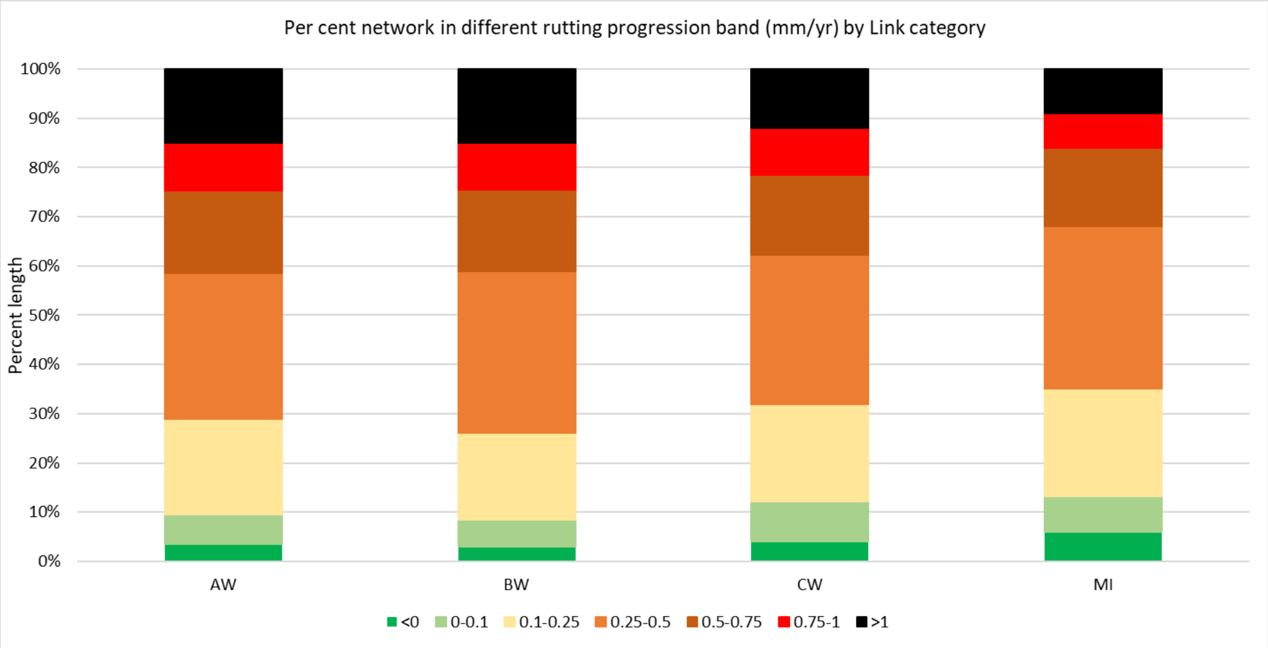
2.5.8 Rut Progression for Link Categories and Combinations

Table 2.17 summarises the average rutting progression for MRWA link categories, and Figure 2.9 displays the % length in different rutting progression bands by link category.

Table 2.17: Average rut progression for road link category

Link category	Average rutting progression (mm/year)
AW	0.56
AW+	0.56
BW	0.55
BW+	0.51
CW	0.50
MFF	0.53
MI	0.45

Figure 2.9: Per cent length in different rut progression band for link categories



Link Category MI has a lower average rut progression rate than the other link categories. This is most likely due to its higher design standards. Also, most of the network lengths in MI sit in lower rut progression bands compared to other link categories.

2.6 Findings from the Analysis

Findings from the analysis under Task 1 are as follows:

- Nearly 14% of the network has a rutting progression rate of more than 1 mm/year.
- A similar rutting distribution across the regions was observed with higher values observed for the Kimberley region. It should be noted that only 66% of the road length in the Kimberley fulfilled the analysis criteria, and this might affect the findings.
- As expected, a lower rut progression rate was found with the higher traffic bands and hence a higher % of road length occurred in lower rut progression bands. Roads carrying higher traffic are generally constructed to higher design standards.
- This observation holds true for link category MI, with this showing lower rates of deterioration and a higher % of road length in the lower rut progression ranges than other link categories.
- The average rutting progression values are similar across pavement age bands. However, pavements constructed after 2014 show higher average rut progression and relatively old pavements show reduced rut progression, a ‘survivor’ effect for old and strong pavements.
- A ‘Very Poor’ PMI is associated with a higher % of road length in higher rut progression bands for selected MRWA regions.
- Higher rainfall does not have much influence on rut progression rates, although the Great Southern and South-West region displayed slightly increased % of road length in the more 1 mm/year rut progression band.
- For all traffic ranges, a higher TMI (corresponding to lower evaporation and higher rainfall) is generally associated with a larger % of road length in the higher rutting progression bands. This observation also holds true at a regional level except for the Metro and Pilbara regions.
- Actual spending on routine maintenance treatments may have had a masking effect on the overall rut progression. Although MMIS values quantify the recorded repair of defects in monetary terms, it does not provide information on actual spending on routine maintenance work done for a particular segment.

These parameters (individual and combinations) demonstrate their influence on rutting progression for the MRWA road network. Additional combinations might also be possible, but do not fall within the scope of the current work. A combined matrix including all parameters was not produced. Such a combination is expected to create a complex table where effects of parameters on rutting progression may not be separated due to the complex interaction between various independent parameters.

3 Task 2 – Development of Rut Progression Model for WA

3.1 General

Task 2 involved the development of rutting models using a full set of load-related and environmental variables, including TSD slope velocity and equivalent deflection data (D0, D200, etc.) to estimate deflection-related parameters. This task also needed to ensure that the dataset represented the range of performance demonstrated and the range of contributing variables in a balanced manner. The outputs from the analysis were at a network level as well as road link category specific modelling equations predicting total rutting as the dependent variable over time.

3.2 Data Processing and Transformation

Model development involved a desktop analysis using a statistical software package (SPSS) and incorporating relevant data inputs defined during the WARRIP IDM2 project and time series performance data under Task 1 as independent variables. MRWA supplied historical pavement rutting data from 2007 to 2016, which was collected bi-annually. A full TSD dataset with deflection information was also supplied for the years 2018 and 2020. The available datasets were initially combined for a general network rutting model and then split into road link categories for separate rutting models if there was sufficient data in each category for statistically significant models.

Similar to Task 1, for each surveyed segment under each supplied condition survey file, the maximum of the 75th percentile rut depth value across the wheelpaths was used as the rutting for that segment for model development purposes. The corresponding columns from the supplied MRWA data and resulting rut depth for modelling is shown in Table 3.1 for a sample segment.

Table 3.1: Rut depth calculation for model development

75P_L_RUT_OWP_AVE	75P_L_RUT_IWP_AVE	75P_R_RUT_OWP_AVE	75P_R_RUT_IWP_AVE	Rut depth for modelling
1.51	4.93	2.76	4.24	4.93

Each data sample had 100 m segmentation (same as the survey) at carriageway level.

Similar to rutting, deflection data was supplied at 100 m intervals. The maximum of maximum deflection (D0) values across the wheelpaths of a segment was used as the deflection for that segment for model development purpose. The corresponding columns from the supplied MRWA data and resulting deflection for modelling is shown in Table 3.2 for a sample segment.

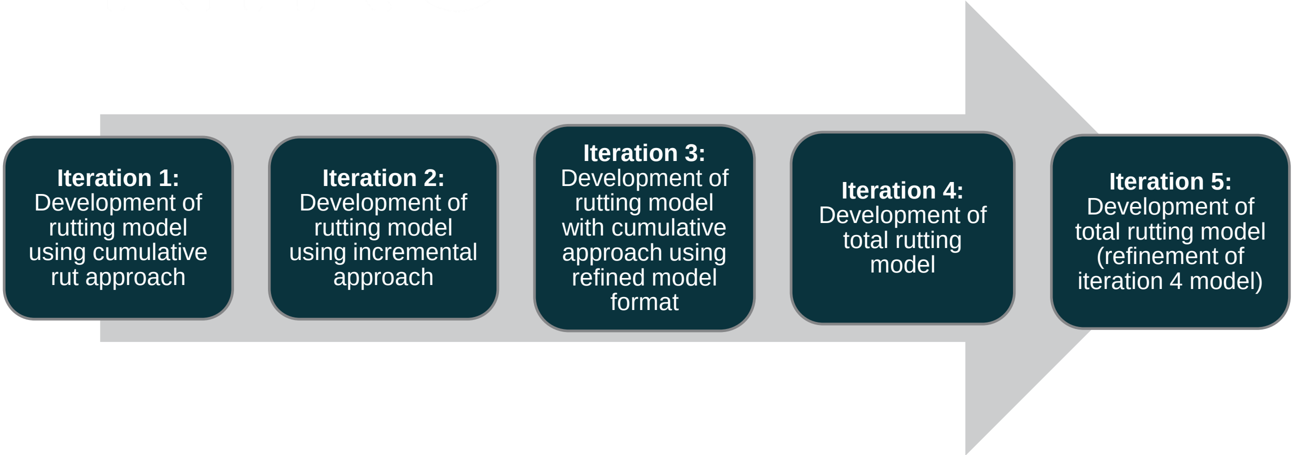
Table 3.2: Deflection D0 calculation for using in the model

L_D0_Max	R_D0_Max	Maximum D0
556.21	605.49	605.49

3.3 Rutting Model Development Approach

The development of the rutting model was an iterative process where different techniques were tested to generate suitable model(s) that included independent variables for pavement age, strength and climate as well as yielding a satisfactory goodness-of-fit to the data. All iterations involved the preparation of suitable data for the analysis and analysing the same in SPSS. Five iterations were completed as outlined in Figure 3.1.

Figure 3.1: Iterations involved in rutting model development



3.4 Iteration 1: Development of Rutting Model Using Cumulative Rut Approach

As a first trial, cumulative rutting at any time (t) as a function of condition, traffic, climate, strength and other variables was attempted. Cumulative rutting is considered as total rutting at any time (t) with the initial rut densification subtracted from it. Data analysis, review and outputs from Iteration 1 are included in Appendix A.1.

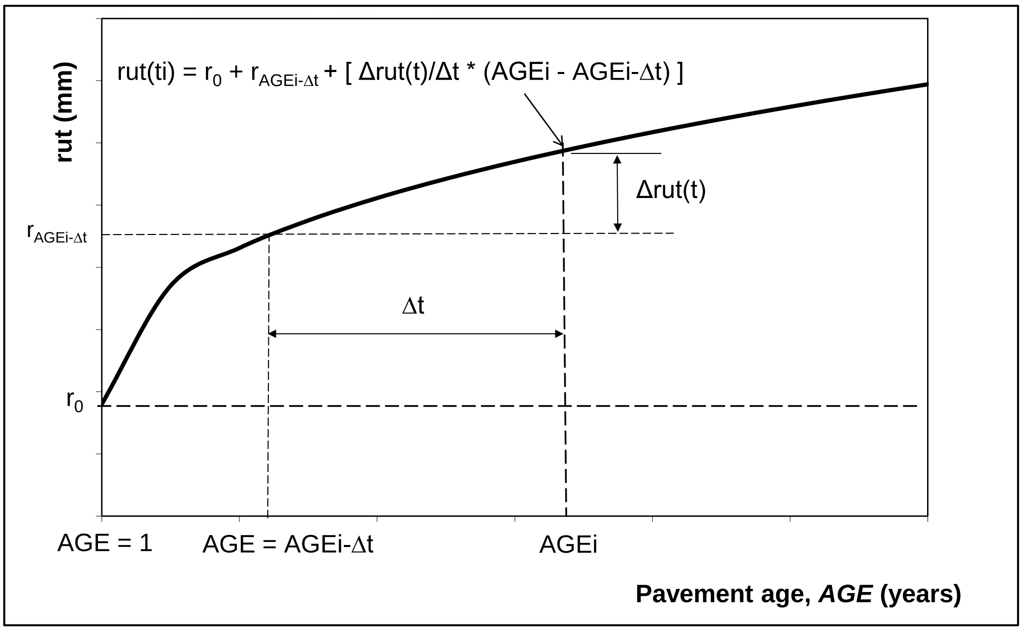
Although few equations in Iteration 1 yielded relatively satisfactory goodness-of-fit (adjusted r^2 of 0.588 for Equation A13 in Appendix A.1.2), none of the equations met the boundary condition of cumulative rutting being 0 (zero) when at pavement age of 1 (as there is only the initial rut densification at pavement age = 1).

Hence, there was a need to further review the equation format. An option was to use the rate of rutting progression as opposed to cumulative rutting to eliminate the issue of meeting the above boundary condition. In addition, during discussion with MRWA, the need to use actual in-service pavement deflection data was stated instead of calculated values. All these issues were accounted for in the subsequent iterations.

3.5 Iteration 2: Development of Incremental Rutting Model

Iteration 2 involved the use of an incremental rut deterioration model form, Equation A14 in Appendix A.2. Incremental rut models estimate the rate of rut progression, $\Delta rut(t)/\Delta t$, as a function of independent variables. A schematic diagram is presented in Figure 3.2. Data analysis, review and outputs from Iteration 2 are included in Appendix A.2.

Figure 3.2: Rate of change of rutting with pavement age



Using the incremental model forms during Iteration 2, all variables were statistically significant. However, the goodness-of-fit of Equation A14 was very low (adjusted r^2 = 0.022) indicating the model had very poor predictive power. This outcome led to Iteration 3.

3.6 Iteration 3: Development of Cumulative Rutting Model Using Refined Format

The difference between Iteration 3 and Iteration 1 was in the use of the model equation format and TSD deflection data. Different equation formats of non-linear regression were tested to predict cumulative rutting (Rut(t) − R0) as a function of various independent variables while maintaining the boundary condition of cumulative rutting being zero at pavement age one. Analysis outputs are included in Appendix A.3.

As observed from Iteration 3 outputs, using pavement age as a multiplier with the rest of the parameters made all other parameters, including pavement age, statistically insignificant. Most of the equations also yielded low adjusted r^2 values. However, only Equation A17 had a reasonable goodness-of-fit (r^2 = 0.57), where age was the only significant variable.

3.7 Iteration 4: Development of Total Rutting Model

Iteration 4 attempted to predict total rutting Rut(t) as a dependent variable in the rut progression model.

All previous iterations did not yield a satisfactory model to predict cumulative rutting over time. Data exploration also showed that most of the WA network pavements have a high pavement age (i.e. > 20 years) with relatively low cumulative rutting (< 10 mm). The impacts of rehabilitation and surface treatment history were accounted for so that only the surveyed rutting data that was free from the effect of maintenance was used. However, there was limited information on the amount of routine maintenance conducted and its influence on rutting progression was not directly accounted for.

There was also uncertainty about the amount of initial densification, R0, due to the lack of new pavements to measure R0. Therefore, R0 was estimated using the HDM-4 formula (Morosiuk, Riley & Odoki 2001) which may not be applicable for WA pavement types and conditions. Hence, the use of cumulative rutting (Rut(t) − R0) does not suit the available data and conditions in WA.

3.7.1 Iteration 4 – Data for Analysis

Input data for Iteration 4 was refined to only include segments with no decrease in total rutting over time as opposed to previous iterations, where a decrease of < 1 mm in successive years was allowed (Section 2.3). This modification resulted in 126,935, 100 m valid analysis segments (meeting all selection criteria used in Section 2.3 with no decrease in rutting over time). For any valid segment, the following steps were undertaken:

- Total rutting data, Rut(t), in each year was used as a data sample.
- Corresponding pavement age, Pavement ageatt, and ESAs, ESAatt, were calculated for those data points.
- Total rutting of 1 mm at pavement age of 1 was assumed due to initial rut densification.
- An average in-service D0 from TSD deflection data was used, with D0-TSDav based on the average of the maximum deflection TSD data from 2018 and 2020.
- Data points with pavement ages greater than 40 years were discarded.

These steps resulted in about 371,000 data samples in SPSS.

3.7.2 Iteration 4 – Analysis in SPSS

Non-linear regression: Equations tested

Six main equation formats (Equations 1 to 6) were tested using a combination of pavement age, strength (deflection), climate and traffic combinations.

$$\text{Total rutting at t} = a1 + a2*(\text{Pavementageatt} - 1)^{\wedge}a3 \quad (1)$$

$$\text{Total rutting at t} = a1 + a2*((\text{Pavementageatt} - 1)^{\wedge}a3)*(1 + \text{D0-TSDav}*a4) \quad (2)$$

$$\text{Total rutting at t} = a1 + a2*((\text{Pavementageatt} - 1)^{\wedge}a3)*(1 + \text{D0-TSDav}*a4 + (100 + \text{TMI})*a5) \quad (3)$$

$$\text{Total rutting at t} = a1 + a2*((\text{Pavementageatt} - 1)^{\wedge}a3)*(1 + \text{D0-TSDav}*a4 + (100+\text{TMI})*a5 + \text{ESAatt}*a6) \quad (4)$$

$$\text{Total rutting at t} = a1 + a2*((\text{Pavementageatt} - 1)^{\wedge}a3)*(1 + (\text{D0-TSDav}*\text{ESAatt})*a4 + (100 + \text{TMI})*a5) \quad (5)$$

$$\text{Total rutting at t} = a1 + a2*((\text{Pavementageatt} - 1)^{\wedge}a3)*(1 + (\text{D0-TSDav}/\text{ESAatt})*a4 + (100 + \text{TMI})*a5) \quad (6)$$

Outputs from the SPSS analyses were as follows:

- All independent variables in Equations 1, 2 and 3 were statistically significant. However, the predictive power of the models increased with the progressive inclusion of independent variables. Equation 3 included the statistically significant variables of pavement age, strength, D0, and the climate variable, TMI.
- Equation 4 included traffic load variable, ESA, in addition to all the variables in Equation 3. The traffic load was significant but had a very small coefficient with a negative sign, implying decreased rutting with increased traffic load.
- Equation 5 also yielded a negative value for coefficient a4, implying the higher the traffic, the lower the total rutting. Traffic load was used as a denominator In Equation 6, and yielded a positive value for a4. This again implies that total rutting was inversely proportional to traffic.

SPSS outputs using Equations 3, 4, 5 and 6 are presented in Figure 3.3.

Figure 3.3: Selected SPSS outputs for Equation 3, 4, 5 and 6

Parameter Estimates

Parameter	Estimate	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
a1	1.023	.006	1.010	1.035
a2	1.525	.016	1.494	1.555
a3	.167	.002	.163	.170
a4	.001	.000	.001	.001
a5	.005	.000	.005	.005

ANOVA[a]

Source	Sum of Squares	df	Mean Squares
Regression	7466799.755	5	1493359.951
Residual	1431968.006	321406	4.455
Uncorrected Total	8898767.761	321411	
Corrected Total	3304178.645	321410	

Dependent variable: Total Rutting (at t)[a]

a. R squared = 1 - (Residual Sum of Squares) / (Corrected Sum of Squares) = .567.

(a) Equation 3

Parameter Estimates

Parameter	Estimate	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
a1	.033	.006	.021	.046
a2	2.293	.018	2.258	2.328
a3	.135	.001	.132	.138
a4	.001	.000	.001	.001
a5	.004	.000	.004	.005
a6	-1.383E-7	.000	-1.490E-7	-1.276E-7

ANOVA[a]

Source	Sum of Squares	df	Mean Squares
Regression	7351147.490	6	1225191.248
Residual	1435227.271	321405	4.465
Uncorrected Total	8786374.761	321411	
Corrected Total	4090310.916	321410	

Dependent variable: TotalRuttingatt[a]

a. R squared = 1 - (Residual Sum of Squares) / (Corrected Sum of Squares) = .649.

(b) Equation 4

Parameter Estimates

Parameter	Estimate	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
a1	1.024	.006	1.011	1.036
a2	2.187	.018	2.152	2.222
a3	.165	.002	.161	.169
a4	-3.660E-11	.000	-5.950E-11	-1.369E-11
a5	.004	.000	.004	.004

ANOVA[a]

Source	Sum of Squares	df	Mean Squares
Regression	7398711.836	5	1479742.367
Residual	1500055.924	321406	4.667
Uncorrected Total	8898767.761	321411	
Corrected Total	3304178.645	321410	

Dependent variable: Total Rutting (at t)[a]

a. R squared = 1 - (Residual Sum of Squares) / (Corrected Sum of Squares) = .546.

(c) Equation 5

Parameter Estimates

Parameter	Estimate	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
a1	1.024	.006	1.011	1.036
a2	2.174	.018	2.139	2.210
a3	.165	.002	.161	.169
a4	.641	.107	.430	.852
a5	.004	.000	.004	.004

ANOVA[a]

Source	Sum of Squares	df	Mean Squares
Regression	7398834.827	5	1479766.965
Residual	1499932.933	321406	4.667
Uncorrected Total	8898767.761	321411	
Corrected Total	3304178.645	321410	

Dependent variable: Total Rutting (at t)[a]

a. R squared = 1 - (Residual Sum of Squares) / (Corrected Sum of Squares) = .546.

(d) Equation 6

As requested by MRWA, 3 of the above 6 equations (3, 5, 6) were also tested by replacing deflection with the average curvature parameter, AvgCurvature (= average(D0-D200TSD)).

- Equation 3 Total rutting at t = a1 + a2*((Pavementageatt - 1)^a3)*(1 + AvgCurvature*a4 + (100 + TMI)*a5)
- Equation 5 Total rutting at t = a1 + a2*((Pavementageatt - 1)^a3)*(1 + (AvgCurvature *ESAatt)*a4 + (100 + TMI)*a5)
- Equation 6s Total rutting at t = a1 + a2*((Pavementageatt - 1)^a3)*(1 + AvgCurvature/ESAatt)*a4 + (100 + TMI)*a5)

All equation formats yielded lower adjusted r^2 values when deflection was replaced by curvature. The corresponding adjusted r^2 values from SPSS outputs are presented in Figure 3.4.

Figure 3.4: SPSS output-r^2 values for Equation 3, 5 and 6 (deflection replaced by curvature)

ANOVA[a]

Source	Sum of Squares	df	Mean Squares
Regression	8471123.001	5	1694224.600
Residual	1641041.840	363772	4.511
Uncorrected Total	10112164.84	363777	
Corrected Total	3722969.352	363776	

Dependent variable: Total Rutting (at t)[a]

a. R squared = 1 - (Residual Sum of Squares) / (Corrected Sum of Squares) = .559.

Equation 3

ANOVA[a]

Source	Sum of Squares	df	Mean Squares
Regression	8404405.885	5	1680881.177
Residual	1707758.956	363772	4.695
Uncorrected Total	10112164.84	363777	
Corrected Total	3722969.352	363776	

Dependent variable: Total Rutting (at t)[a]

a. R squared = 1 - (Residual Sum of Squares) / (Corrected Sum of Squares) = .541.

Equation 5

ANOVA[a]

Source	Sum of Squares	df	Mean Squares
Regression	8403513.641	5	1680702.728
Residual	1706915.261	363772	4.692
Uncorrected Total	10110428.90	363777	
Corrected Total	3722524.777	363776	

Dependent variable: Total Rutting (at t)[a]

a. R squared = 1 - (Residual Sum of Squares) / (Corrected Sum of Squares) = .541.

Equation 6

Equation 5, using AvgCurvature and ESA, showed a very low (3*10^-10) but positive coefficient for a4 (for the AvgCurvature-ESA combination), although such low values will have zero to no impact on total rutting estimates.

3.7.3 Selected Modelling Equation (Full Network Sample) – Iteration 4

Considering all analysis equation formats tested in Iteration 4, Equation 7, using pavement age, deflection and TMI, offered the model with the best predictive power. The corresponding modelling equation is:

Total rutting at t = 1.02 + 1.525*((Pavementageatt - 1)^0.167)*(1 + D0-TSDav*0.001 + (100 + TMI)*0.005) 7

Plotting of the selected rutting model and a comparison against the Austroads model was also conducted (Austroads 2010b). Also, link category and road type-specific models were developed using the Equation 7 form. All of these models are shown in Appendix A.4. Initial testing and validation of the developed model was also conducted using training and test data.

However, further validation using an incremental form of the selected model revealed the low predictive capability of the model due to very flat rate of rutting progression compared to observed deterioration within the MRWA road network. Hence, the model was further refined by iteration 5.

3.8 Iteration 5: Total Rutting Model – Refined Iteration 4 Equation

Iteration 5 attempted to predict total rutting Rut(t) as a dependent variable in the rut progression model.

3.8.1 Iteration 5 – Data for Analysis

Input data for iteration 5 was the same as that used in Iteration 4 except for deflection. During Iteration 4, an average deflection (from 2018 and 2020 TSD data collection) was used per segment and assigned to all years with collected data. This effectively assumed a constant value of maximum deflection (D0) for a segment. For iteration 5, time series deflection was estimated based on a 50 micron decrease in deflection/year for the preceding years using the 2018/2020 data[1]. The use of time series deflection was expected to increase the predictive capability of the model due to an increase in deflection with time. About 371,000 data samples were used in the SPSS model analysis for iteration 5 (same as Iteration 4).

3.8.2 Iteration 5 – Analysis in SPSS

Equation 7 from Iteration 4 using pavement age, TSD deflection, D0(t), and TMI produced the model with the best predictive power. However, the model had a asymptotic affect with age resulting in a lower rate of annual increment. Hence, the modelling equation format of Equation 7 was changed during Iteration 5 as shown by Equation 8. Selected SPSS output using the revised format is presented in Figure 3.5.

$$\text{Total rutting at t} = a1 + a2*(\text{Pavementageatt} - 1)*(1 + D0(t)*a3 + (100 + TMI)*a4) \quad 8$$

It should be noted that D0(t) is a time-series deflection based on the assumption that an annual 50 micron increase in deflection D0 occurs. This assumption may not be appropriate across the whole MRWA network.

Figure 3.5: Selected SPSS output for the revised equation format

Parameter Estimates

Parameter	Estimate	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
a1	1.880	.006	1.869	1.892
a2	.061	.001	.060	.063
a3	.002	.000	.001	.002
a4	.012	.000	.011	.012

ANOVA[a]

Source	Sum of Squares	df	Mean Squares
Regression	8250708.573	4	2062677.143
Residual	2042006.363	371216	5.501
Uncorrected Total	10292714.94	371220	
Corrected Total	3781296.710	371219	

Dependent variable: Total Rutting (at t)[a]

a. R squared = 1 - (Residual Sum of Squares) / (Corrected Sum of Squares) = .460.

3.9 Total Rutting Model – Full Network

Based on Equation 8, the selected total rutting modelling equation for the full network is as follows:

$$\text{Total rutting at t} = 1.88 + 0.061*(\text{Pavementageatt} - 1) *(1 + D0(t)*0.002 + (100 + TMI)*0.012) \quad 9$$

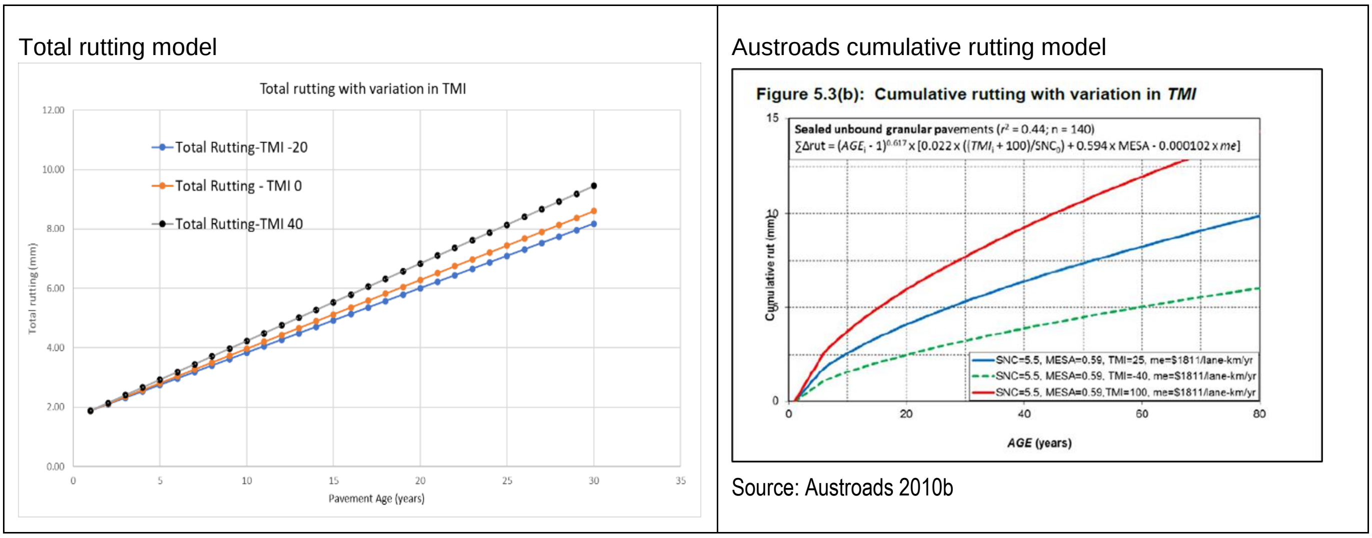
Though the fit of the Equation 9 model decreased slightly compared with the Equation 7 model by iteration 4, the rate of rutting progression over time was more realistic and fitted the observations better as found during Task 3 and Task 4 (Section 4 and Section 5).

[1] Earlier analysis of deflection data revealed that two-thirds of the MRWA network had a deflection increase of 100 micron over the 2 year period (2018–2020).

3.9.1 Plotting of the Rutting Model and Comparison Against Austroads Model

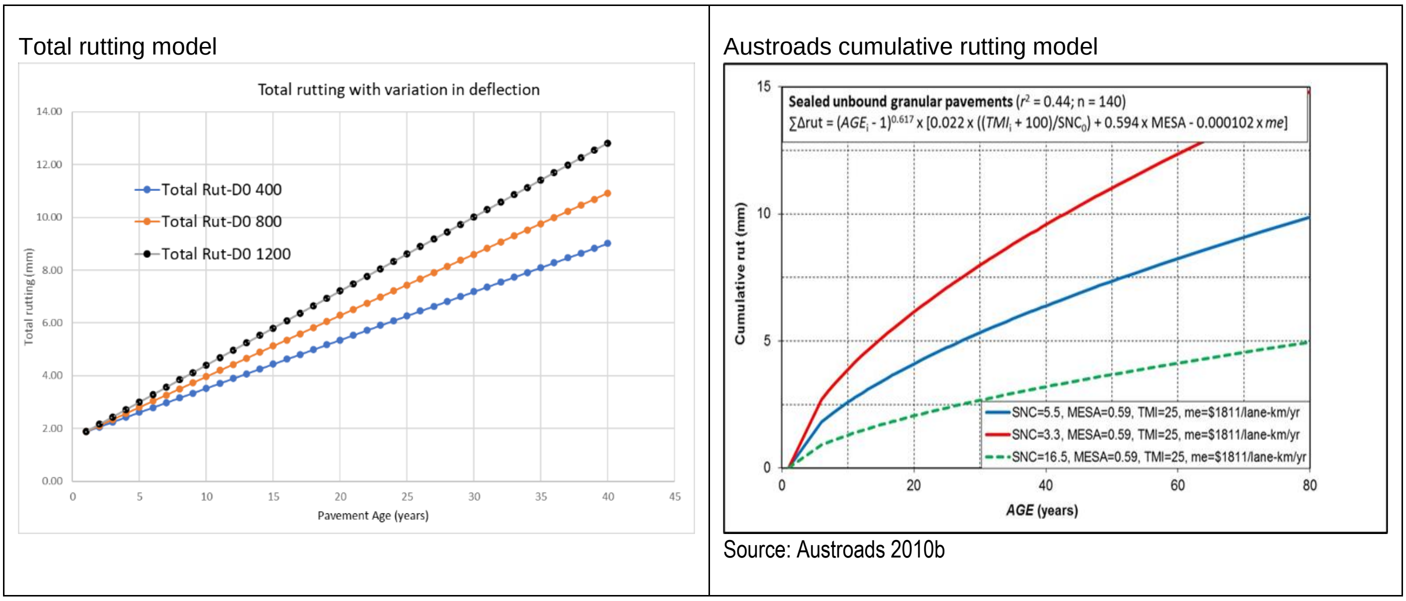
The selected modelling equation was plotted by varying age, climate and deflection and compared against the Austroads models (Austroads 2010b). The results are shown in Figure 3.6 and Figure 3.7.

Figure 3.6: Plotting of total rutting (using selected equation) by varying TMI (deflection = 800 micron) and comparison with Austroads cumulative rut model



Source: Austroads 2010b

Figure 3.7: Plotting of total rutting (using selected equation) by varying deflection (TMI = 0) and comparison with Austroads cumulative rut model



Source: Austroads 2010b

The results show that:

- the developed total rutting model Equation 9 is sensitive to the changes in climate.
- the developed total rutting model Equation 9 is sensitive to the changes in deflection.
- rutting progression shows a linear trend of increases over time (pavement age) without a reduced rate of rutting effect.

3.9.2 Total Rutting Model for MRWA Road Link Categories

The selected model was also tested in SPSS by separating samples for each MRWA road link category to explore if the significance of the parameters as well as regression coefficient changes for different road link categories. The SPSS sample sizes for 4 MRWA link categories are presented in Table 3.3.

Table 3.3: SPSS samples under each road link

Link category	No of samples
AW (includes AW and AW+ road links)	74,530
BW (includes BW and BW+ road links)	188,145
CW	75,189
MI (includes MI and MFF road links)	33,104

SPSS outputs for AW, BW and CW road link categories using the selected equation are presented in Figure 3.8. Some changes in the regression coefficient values were observed for each link category although they are not large, except for a4 (coefficient for TMI) for the CW link category. Improvement in modelling predictions (adjusted r^2 values) were also attained for all 3 link categories compared to the full network sample result. CW link category has the highest adjusted r^2 values among the 3 link categories.

Figure 3.8: SPSS outputs using selected equation for link category AW BW and CW

Parameter Estimates

Parameter	Estimate	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
a1	1.889	.013	1.863	1.915
a2	.072	.002	.068	.075
a3	.002	.000	.002	.002
a4	.008	.000	.007	.009

ANOVA[a]

Source	Sum of Squares	df	Mean Squares
Regression	1796257.276	4	449064.319
Residual	429876.874	74525	5.768
Uncorrected Total	2226134.150	74529	
Corrected Total	832387.603	74528	

Dependent variable: Total Rutting (at t)[a]

a. R squared = 1 - (Residual Sum of Squares) / (Corrected Sum of Squares) = .484.

(a) AW

Parameter Estimates

Parameter	Estimate	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
a1	1.832	.008	1.817	1.848
a2	.023	.001	.021	.025
a3	.003	.000	.003	.004
a4	.054	.003	.047	.060

ANOVA[a]

Source	Sum of Squares	df	Mean Squares
Regression	4240662.211	4	1060165.553
Residual	1019321.618	188140	5.418
Uncorrected Total	5259983.830	188144	
Corrected Total	1956080.469	188143	

Dependent variable: Total Rutting (at t)[a]

a. R squared = 1 - (Residual Sum of Squares) / (Corrected Sum of Squares) = .479.

(b) BW

Parameter Estimates

Parameter	Estimate	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
a1	1.768	.012	1.745	1.791
a2	.023	.002	.018	.028
a3	.005	.001	.004	.007
a4	.063	.008	.047	.079

ANOVA[a]

Source	Sum of Squares	df	Mean Squares
Regression	1594460.188	4	398615.047
Residual	335094.947	75184	4.457
Uncorrected Total	1929555.135	75188	
Corrected Total	668125.153	75187	

Dependent variable: Total Rutting (at t)[a]

a. R squared = 1 - (Residual Sum of Squares) / (Corrected Sum of Squares) = .498.

(c) CW

The model equations for total rutting for AW, BW and CW are given in Equations 10, 11 and 12:

Link category AW: 10

Total rutting at t = 1.88 + 0.072*(Pavementageatt – 1) *(1 + D0(t)*0.002 + (100 + TMI)*0.008)

Link category BW: 11

Total rutting at t = 1.83 + 0.023*(Pavementageatt – 1) *(1 + D0(t)*0.003 + (100 + TMI)*0.054)

Link category CW: 12

Total rutting at t = 1.77 + 0.023*(Pavementageatt – 1) *(1 + D0(t)*0.005 + (100 + TMI)*0.063)

However, link category MI (including MFF) produced an unsatisfactory output for the selected modelling equation with negative coefficients for all parameters. MI is the link category with the highest design standards (relatively high strength than the rest of the link categories) and less susceptible to climate variation. Hence a revised equation (excluding TMI) was tested on this sample to explore if the pavement age and deflection were significant parameters or not.

The two equations format tested on MI/MFF subnetwork were:

1. a1 + a2*(Pavementageatt – 1)*(1 + a3*D0(t) + a4*(100 + TMI))
2. a1 + a2*(Pavementageatt – 1)*(1 + a3*D0(t)).

SPSS outputs for MI using both these equations are presented in Figure 3.9.

Figure 3.9: SPSS outputs using selected equation for link category MI

Parameter Estimates

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
a1	2.170	.020	2.130	2.210
a2	-.022	.004	-.029	-.014
a3	-.009	.002	-.013	-.006
a4	-.033	.004	-.042	-.024

ANOVA[a]

Source	Sum of Squares	df	Mean Squares
Regression	669277.768	4	167319.442
Residual	197631.037	33099	5.971
Uncorrected Total	866908.805	33103	
Corrected Total	319092.864	33102	

Dependent variable: Total Rutting (at t)[a]

a. R squared = 1 - (Residual Sum of Squares) / (Corrected Sum of Squares) = .381.

Equation format 1

Parameter Estimates

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
a1	2.175	.021	2.135	2.216
a2	.061	.001	.058	.063
a3	.004	.000	.003	.004

ANOVA[a]

Source	Sum of Squares	df	Mean Squares
Regression	666131.113	3	222043.704
Residual	200777.692	33100	6.066
Uncorrected Total	866908.805	33103	
Corrected Total	319092.864	33102	

Dependent variable: Total Rutting (at t)[a]

a. R squared = 1 - (Residual Sum of Squares) / (Corrected Sum of Squares) = .371.

Equation format 2

Equation format b produced a better outcome with both pavement age and deflection being significant parameters. The final modelling equation for link category MI is as follows (Equation 13).

Total rutting at t = 2.17 + 0.061*(Pavementageatt – 1)*(1 + D0(t)*0.004) 13

3.10 Limitations of the Developed Model

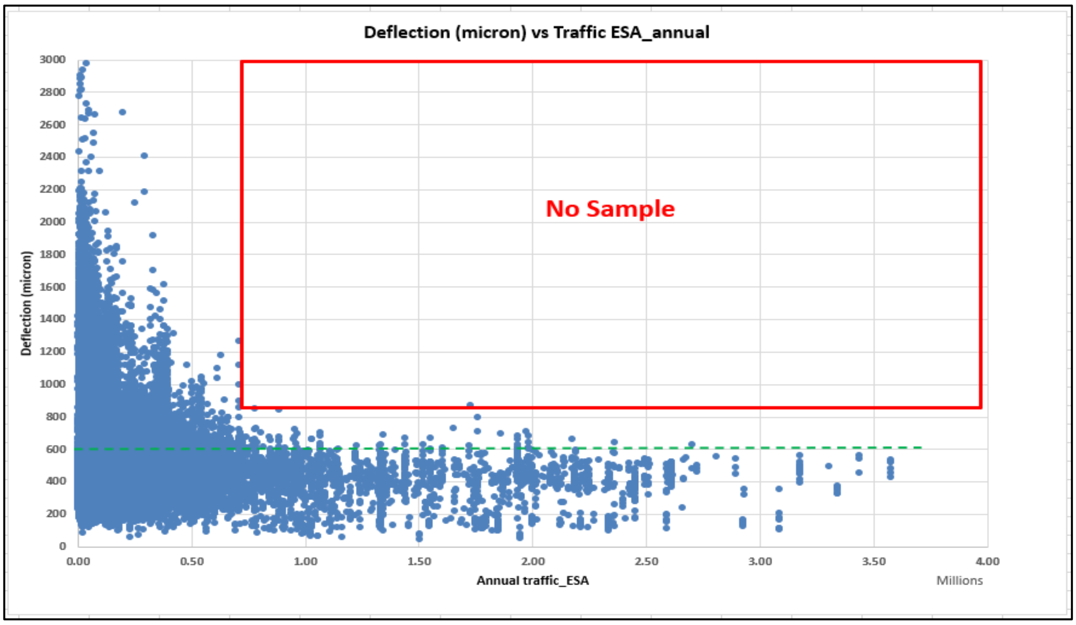
The outputs from this modelling task are:

- a total rutting model for the full MRWA network
- refined total rutting models for each MRWA link category.

Models were developed using the full network MRWA data which included pavement strength, traffic, pavement age, etc. and their combinations as observed in WA. However, these models did not contain all the possible independent variables of other traffic and pavement strength parameters.

A scatter plot of deflection vs Annual ESA (at t) for the analysed sample is presented in Figure 3.10.

Figure 3.10: Deflection vs ESA (at t) plot of all SPSS data samples



Around 66% of the analysed data samples had a TSD deflection (D0) less than 600 micron. A vast majority of these samples also sat within a low traffic range of annual ESA less than 1 million. Only 7% of the analysed samples had deflection D0 more than 1,000 microns. There were hardly any samples with a high/moderate combination of deflection (deflection over 800 micron) carrying moderate/high traffic (more than 1 million ESAs).

Hence the model should only be applied within the conditions it was developed and should not be extended for the conditions such as:

- pavements with low strength (deflection over 1,000 micron) carrying moderate to high traffic (annual ESAs over 1.5 million) as there were no samples of these variable combinations.
- pavements with moderate strength (deflection in between 800–1,000 micron) carrying moderate to high traffic (annual ESAs over 1 million) as there were a low number of samples of these variable combinations.

4 Task 3 – Testing and Validation of the Developed Model

4.1 General

Task 3 involved desktop-based testing and validation of the developed total rutting model, Equation 9, against observed deterioration. A comparison was made between the predicted rutting value at any given point of time, using the developed total rutting model, with the measured rutting value. This was done using both the training dataset (dataset used in developing the rutting model) and the test dataset (dataset excluded from the rutting model development).

An earlier validation was done using a total rutting model in Iteration 4 and these results shown are in Appendix B. This section includes the results of updated testing and validation using the final refined model (Iteration 5).

4.2 Testing and Validation Approach of the Rutting Model

The developed network-level rut model was tested and validated against the observed deterioration. The validation was conducted in 2 steps:

- Approach–1 – Using the training dataset.
- Approach–2 – Using the test dataset.

4.2.1 Approach 1: Using the Training Dataset

Approach 1 involved testing using the dataset used to develop the total rutting model, the 'training dataset'. Based on the network level Equation 9 model (Section 3.9), the validation steps involved the following:

- Calculated (i.e., predicted) total rutting for each sample using the independent parameters for that sample (age, deflection, TMI).
- Prepared a scatter plot of observed (i.e., measured total rutting) vs predicted total rutting using all analysed samples.
- Prepared cumulative distributions of both observed and predicted total rutting.
- Calculated the absolute differences between observed and predicted rutting as follows:
  - differences in rutting values (mm)
  - differences relative to observed rutting (%).
- Created ranges for the differences to determine analysed training dataset samples in different rutting ranges.

Figure 4.1 and Figure 4.2 display the scatter plot of the observed vs predicted total rutting and the cumulative distributions for the observed and predicted rutting respectively. The scatter plot shows considerable spread between observed and predicted rutting. This is expected as the predictive power of the network-level rutting model is moderate (adjusted r^2 = 0.46). Cumulative distributions reveal 80% of the analysed sample have total rutting of around 8 mm from both observed and predicted rutting. However, some overprediction and underprediction (using the model Equation 9) was observed for samples with rutting below and above 6 mm respectively.

Figure 4.1: Observed vs predicted total rutting – training dataset

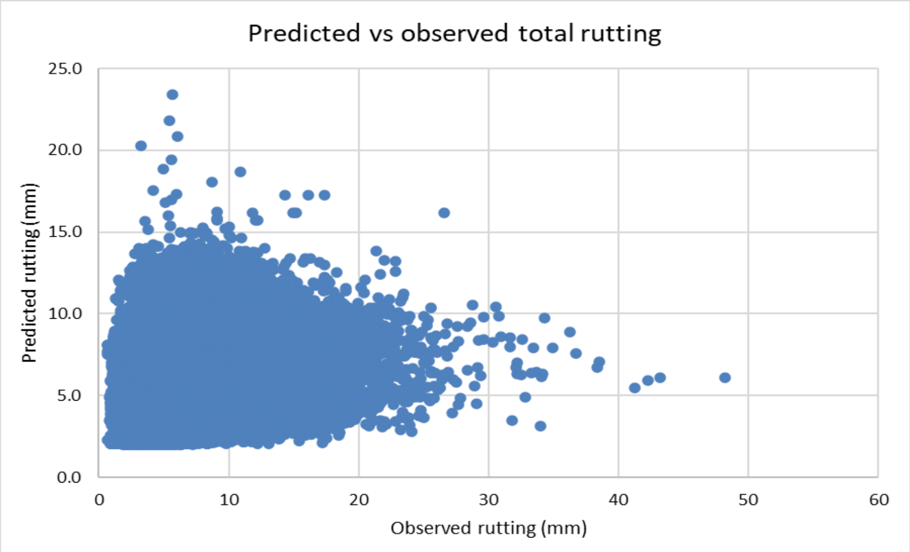


Figure 4.2: Cumulative total rutting distribution plots – observed and predicted total rutting – training dataset

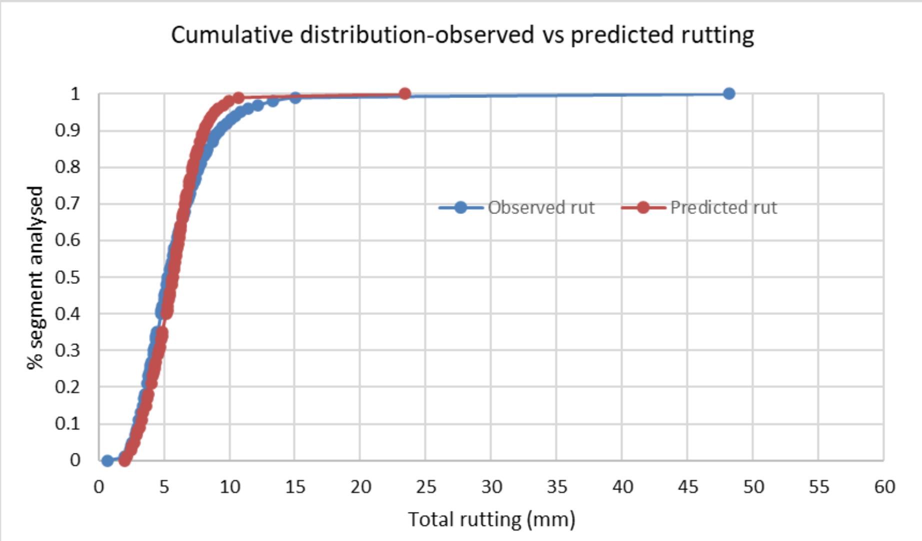


Figure 4.3 and Figure 4.4 display the differences (absolute as well as percentage respectively) between observed vs predicted total rutting using all analysed training dataset samples.

Figure 4.3: Absolute differences between observed and predicted total rutting – training dataset

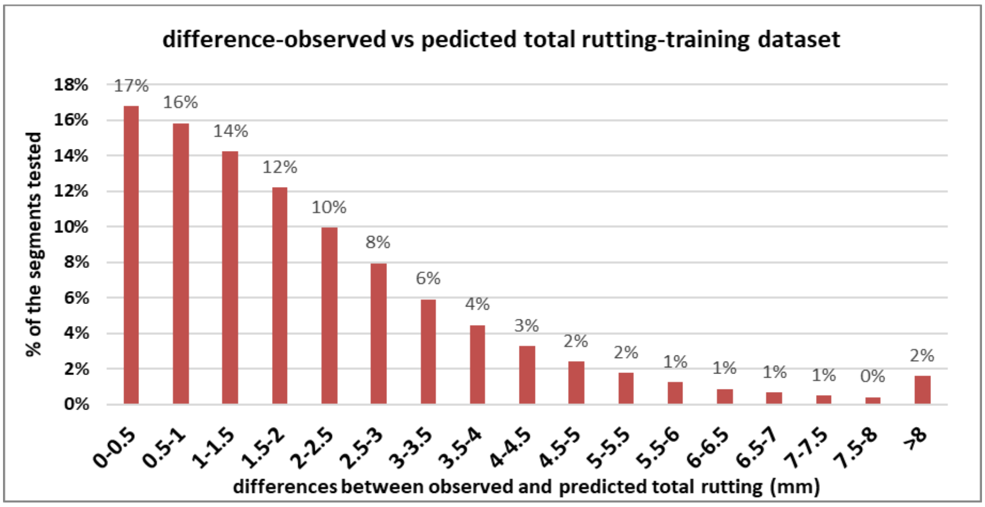


Figure 4.4: Per cent Differences between observed and predicted total rutting – training dataset

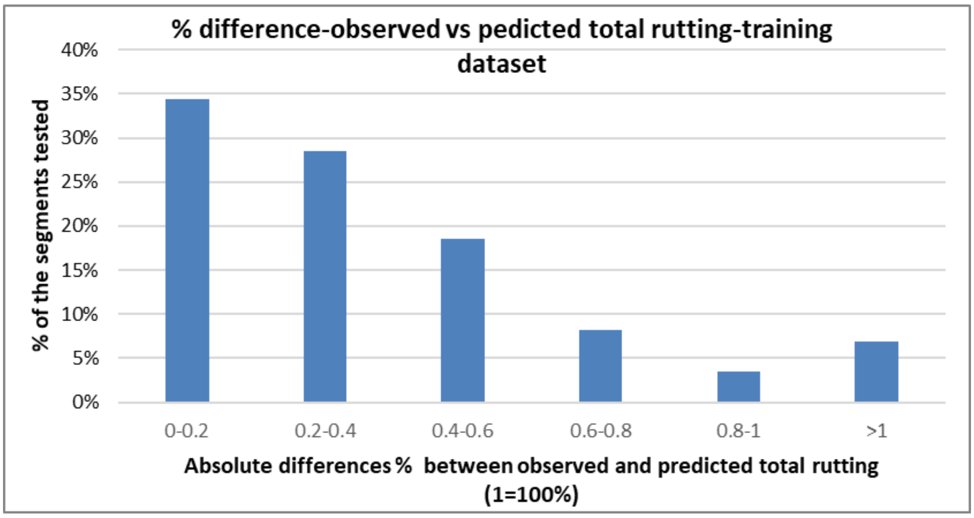


Figure 4.3 shows that, in terms of absolute rutting values, the differences between the observed and predicted rutting were less than 1 mm for 33% of the samples. For the remaining 76% of the rutting samples, the differences between the observed and predicted rutting were within 3 mm. For 2% of the rutting samples, the difference between observed and predicted rutting was more than 8 mm.

Figure 4.4 shows that in terms of percentages, the difference between observed and predicted values was within 20% for 35% of the analysed samples. There were less than 7% of the samples where the differences were more than 100%.

4.2.2 Approach 2: Using the Test Dataset

Approach 2 of the testing involved working with the dataset discarded during model development process. Based on selected network level (Section 3.7) Equation 9, the validation steps involved the following:

- From the discarded dataset in Section 3, segment samples where 2 consecutive years that were free from maintenance affects were filtered out for testing and validation. This data represents the 'test data set'.
- Each data point from the above segments was used as a sample, and from the data supplied, the corresponding pavement age was calculated.
- Using the selected total rutting Equation 9 model, the predicted total rutting for each sample was estimated using the independent parameters for that segment (age, deflection, TMI).
- Prepared a scatter plot of observed (i.e., measured total rutting) vs predicted total rutting using the samples (around 45,000 samples).
- Prepared a cumulative distribution of both the observed and predicted total rutting.
- Calculated the absolute differences between the observed and predicted rutting as follows:
  - differences in rutting values (mm)
  - differences relative to observed rutting (%).
- Created ranges for the differences between the observed and predicted rutting to distribute the analysed test dataset samples into different rutting ranges.

Figure 4.5 and Figure 4.6 display the scatter plots of observed vs predicted total rutting and cumulative total rutting distributions for both respectively, using the test data samples. The scatter plot shows considerable spread between observed and predicted rutting. This is expected as the predictive power of the network-level rutting model is moderate (adjusted r^2 = 0.46). In addition, as this comparison is based on the test data (data not used to develop the model), the accuracy is expected to be less than the training data.

The cumulative distribution shown in Figure 4.6 of the observed rutting data reveal 80% of the analysed samples have observed total rutting of around 9 mm. However, the model predicts the same, estimating a total rutting of around 8 mm for 80% of the analysed test dataset samples.

Figure 4.5: Observed vs predicted total rutting – test dataset

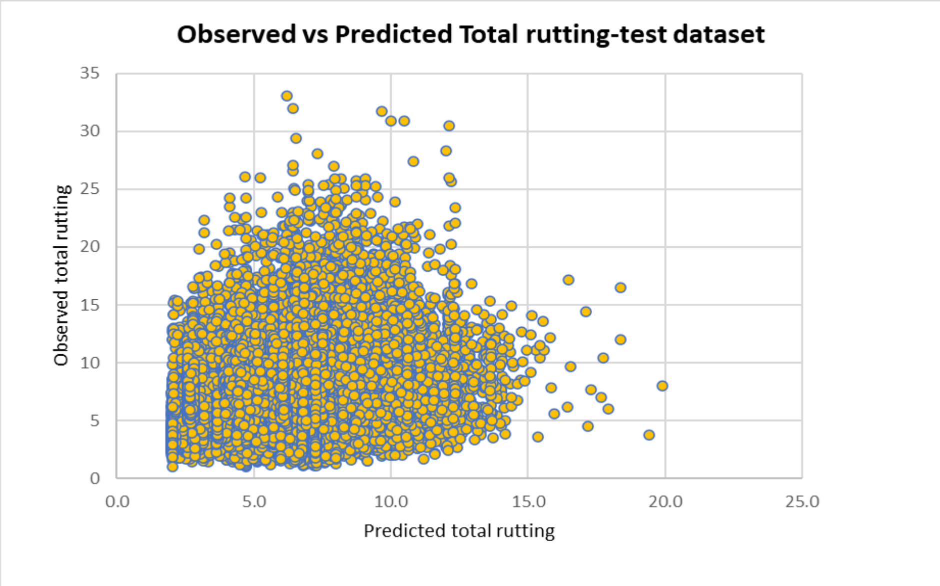


Figure 4.6: Cumulative distribution plots – observed and predicted total rutting – test dataset

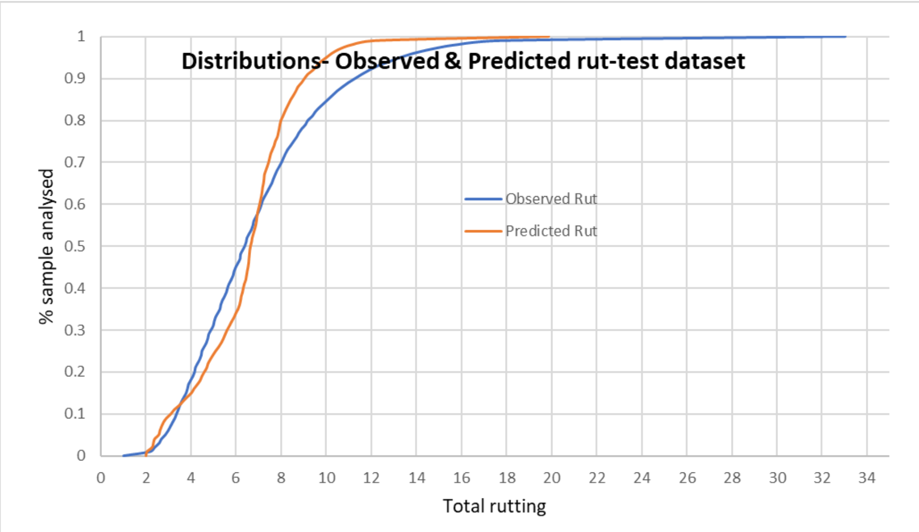


Figure 4.7 and Figure 4.8 display the differences (absolute values as well as percentage respectively) between observed vs predicted total rutting using analysed test dataset samples.

Figure 4.7: Absolute differences between observed and predicted total rutting – test dataset

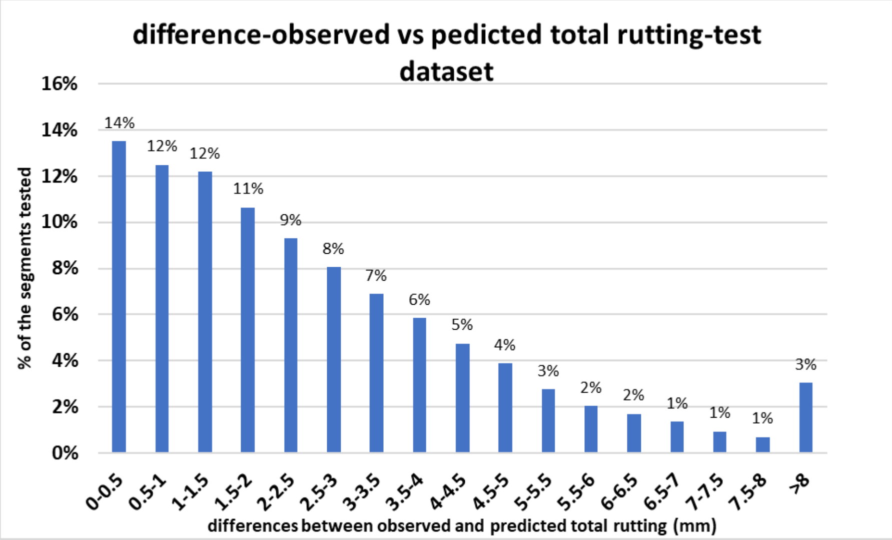
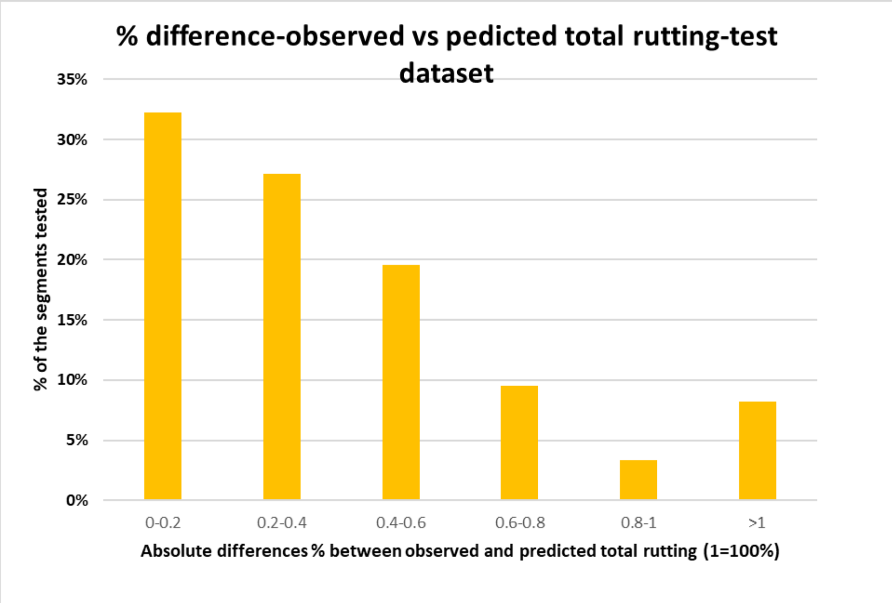


Figure 4.8: Per cent differences between observed and predicted total rutting – test dataset



In terms of absolute values, the differences between the observed and predicted rutting were less than 1 mm for 24% of the samples, compared to 33% using the training data. For 49% of the samples, the difference between the observed and predicted rutting was within 2 mm. Some 3% of samples displayed a difference between the observed and predicted rutting of more than 8 mm. Since this comparison was based on the test data, the resulting accuracy was less than the training data.

In terms of percentages, for 32% of the analysed test dataset samples, the difference between observed and predicted values was within 20%. There were around 8% of the samples where the differences were more than 100%.

5 Task 4 – Further Validation of the Developed Model

5.1 General

The predicted rate of change in rutting for 2 WA regions was also compared against the rate of change from the observed data. The comparison was done using the estimated rate of rutting progression for 2 selected WA regions that had similar matrices as developed during Task 1. The comparison involved a review of the proportions of rutting samples in different rut ranges with both the observed and predicted data.

This section includes validation completed using final refined model (Iteration 5) of Equation 9. However, the limitations found while validating using the Iteration 4 model (that led to the refinement of the model) is outlined in Section 5.2.2.

5.2 Comparison of the Predicted Rate of Rutting with Observed Rate of Rutting

During Task 1, performance matrices were developed for each WA region to determine the rate of change of rutting and % road length in different rut rate ranges. Under Approach 1, similar matrices for 2 selected WA regions (Goldfields-Esperance and Wheatbelt) were prepared using the predicted rutting and its rate of progression over time. These estimates were then compared against the same matrices prepared using observed data. Since no region-specific model was developed, the network level model for total rut prediction was used for this task. A cumulative model form was used to determine the total rutting at any given point of time, while an incremental form of the model was used to determine the rate of rutting progression.

The incremental model form based on the Equation 9 network-level total rut model is expressed as follows (Equation 14):

$$\Delta rut(t) = (1.88 + 0.061*((Pavementageatt(t) - 1)\ )*(1 + D0(t)*0.002 + (100 + TMI)*0.012)) - (1.88 + 0.061*((Pavementageatt(t - 1) - 1)\ )*(1 + D0(t\text{-}1)*0.002 + (100 + TMI)*0.012)) \quad (14)$$

5.2.1 Data Used for the Analysis

The developed network-level model requires the availability of parameters such as TSD deflection, TMI, and pavement age to predict deterioration. Hence the rate of rut progression was estimated using the data under Task 3 (includes both training and test data) as it includes all parameters required for predicting rutting.

The performance matrices development during Task 1 used a wider dataset (without excluding ages > 40 years, sections without deflection, and sections with some rutting fluctuations (< 1 mm)). In order to make the comparison valid, data used during Task 3 is used to reproduce the matrices for observed data and compared against the predicted rates using the same dataset. The length coverage for the regions in this dataset is outlined in Table 5.1.

Table 5.1: Network length from regions used for model validation

Region	Total length (km)	No of analysed 100 m segments	Length analysed (km, approx.)	Coverage
Goldfields-Esperance	2,489.31	12,964	1,296.40	52%
Wheatbelt	3,022.18	11,344	1,134.40	38%

5.2.2 Analysis Outputs – Using Iteration 5 Model

The observed rate of rutting progression was calculated for each analysis segment using the time series data. The predicted rate of rutting progression was estimated for each segment using the increment model form of Equation 14 based on using Equation 7. The percentage of the analysed segments in different rutting ranges using both predicted and observed rutting data are outlined in Table 5.2 and Table 5.3.

Table 5.2: Per cent segments in different rutting progression rates (predicted data)

Region	Rutting progression rate					
	0–0.1	0.1–0.25	0.25–0.5	0.5–0.75	0.75–1	> 1
Goldfields Esperance	91%	5%	1%	1%	2%	2%
Wheatbelt	87%	7%	2%	0%	1%	2%

Table 5.3: Per cent segments in different rutting progression rates (observed data)

Region	Rutting progression rate					
	0–0.1	0.1–0.25	0.25–0.5	0.5–0.75	0.75–1	> 1
Goldfields Esperance	3%	15%	34%	19%	11%	18%
Wheatbelt	3%	13%	29%	20%	12%	23%

The iteration 4 model of Equation 7 predicts a very low rate of rutting progression (< 0.1 mm/year) for more than 85% of the analysed network of both region while the observed data shows segments are spread across different rate of rutting progression bands. This implies that the iteration 4 model in its incremental form performs poorly in predicting the observed rate of deterioration. This finding led to the refinement of the model as shown in Section 3.8. Following sections summarises the validation done using final refined model.

5.2.3 Analysis Outputs – Using Selected Model (Iteration 5)

Total rutting for each analysed segment was estimated using the model form of Equation 9 and compared against the observed total rutting for each year where no maintenance was conducted. The average total rutting for the regions for the different years of data collection using both observed and predicted values are presented in Table 5.4.

Table 5.4: Average total rutting for the regions (observed and predicted values) in different years

Region name	Year	Avg. observed total rutting (mm)	Average predicted total rutting (mm)
Goldfields Esperance	2007	6.4	5.3
	2009	6.3	5.1
	2012	5.5	4.9
	2014	6.4	5.2
	2016	5.8	5.6
	2018	8.0	6.1
	2020	8.6	6.3
Wheatbelt	2007	5.4	6.7
	2009	6.4	6.3
	2012	5.2	4.5
	2014	5.6	5.3
	2016	6.0	5.6
	2018	7.7	5.4
	2020	8.4	5.7

The predicted average total rut values align well with the observed total rutting with some differences consistent over time. This matches with the findings from the network level validation done under Task 3. Additional pavement age ranges were added to check the variations across different age groups (Table 5.5).

Table 5.5: Average total rutting for the regions (observed and predicted values) in different years for various pavement age groups

Region name	Year	Pavement age (at t)	Avg observed total rutting (mm)	Average predicted total rutting(mm)
Goldfields Esperance	2007	0–9	3.8	2.6
		10–19	5.6	3.7
		20–29	6.3	5.1
		30–39	6.5	6.3
	2009	0–9	4.0	2.4
		10–19	4.4	3.5
		20–29	6.2	5.3
		30–39	7.2	6.5
	2012	0–9	3.3	2.6
		10–19	4.6	3.8
		20–29	7.3	5.6
		30–39	6.3	6.4
	2014	0–9	4.2	2.9
		10–19	5.7	4.2
		20–29	6.8	5.9
		30–39	7.7	6.9
	2016	0–9	4.1	3.0
		10–19	5.0	4.2
		20–29	6.0	6.1
		30–39	7.3	7.6
	2018	0–9	5.6	2.5
		10–19	6.0	4.3
		20–29	8.3	6.3
		30–39	10.1	8.2
	2020	0–9	6.0	2.7
		10–19	6.4	4.3
		20–29	8.5	6.2
		30–39	10.6	8.3
Wheatbelt	2007	0–9	4.7	2.6
		10–19	4.4	3.4
		20–29	5.0	5.0
		30–39	4.9	6.5
	2009	0–9	4.2	2.5
		10–19	4.9	3.6
		20–29	5.8	5.1
		30–39	6.2	6.7
	2012	0–9	3.8	2.6
		10–19	5.0	3.8

Region name	Year	Pavement age (at t)	Avg observed total rutting (mm)	Average predicted total rutting(mm)
		20–29	5.6	5.2
		30–39	6.3	7.1
	2014	0–9	4.3	2.6
		10–19	5.5	4.0
		20–29	6.2	5.2
		30–39	6.3	7.2
	2016	0–9	4.7	2.7
		10–19	5.6	4.2
		20–29	6.1	5.4
		30–39	6.4	7.6
	2018	0–9	6.5	2.9
		10–19	7.3	4.3
		20–29	8.3	5.8
		30–39	8.8	8.0
	2020	0–9	6.7	2.8
		10–19	7.9	4.5
		20–29	9.0	6.2
		30–39	9.7	7.9

The iteration 5 model tended to predict rutting well with some variation where the pavement was less than 30 years old. It seems to underpredict rutting for older pavements in the age group of over 30 years where the observed total rutting was substantially higher than the predicted rutting. This seems to be due to the linear nature of the developed model while the observed rutting values at higher pavement ages were not necessarily following a linear trend.

The observed rate of rutting was calculated for each analysis segment using the time series data. The predicted rate of rutting was estimated for each segment using the incremental model of Equation 14. The percentage of the analysed segments in different rutting ranges using both predicted and observed rutting data are outlined in Table 5.6 and Table 5.7.

Table 5.6: Per cent segments in different rutting rates (predicted data)

Region	Rutting progression rate					
	0–0.1	0.1–0.25	0.25–0.5	0.5–0.75	0.75–1	> 1
Goldfields Esperance	0%	44%	55%	1%	0%	0%
Wheatbelt	0%	55%	42%	4%	0%	0%

Table 5.7: Per cent segments in different rutting rates (observed data)

Region	Rutting progression rate					
	0-0.1	0.1-0.25	0.25-0.5	0.5-0.75	0.75-1	>1
Goldfields Esperance	3%	15%	34%	19%	11%	18%
Wheatbelt	3%	13%	29%	20%	12%	23%

As seen from Table 5.6 and Table 5.7, the percentage of segments in different rutting progression rates between the predicted and observed data is different. Due to the linear nature of the developed model, most of the analysed segments lie within 0–0.1 to 0.5 mm/year rutting rate range. There is around 12% of the analysed network in both regions with a rutting rate of 0.75–1 mm/year which are not detected using the predicted rutting rate. This again explains why the predicted average total rutting values for higher pavement ages were underpredicted compared to the observed average values. Nonetheless, the Table 5.6 results show significant improvements over the predictions based on the Iteration 4 model in Table 5.2.

6 Task 6 – Summary of the Analysis

6.1 Overall Findings

The current ‘Improved decision making’ (IDM3) project was designed to model and validate rutting deterioration prediction on WA roads to provide additional and more tangible benefits to MRWA through more reliable and accurate rutting prediction. Task 1 of the project included the creation of performance matrices of road segments taking the full MRWA network into account to demonstrate similar rutting progression trends with time. The matrices were referenced by the rutting performance (rate of distress) of the road sections. Findings from the analysis under Task 1 are as follows:

- Nearly 14% of the network had a rutting progression rate of more than 1 mm/year.
- Similar rutting distributions across the regions were observed with higher values found for the Kimberley region. It should be noted that around 66% of the road length in the Kimberley met the analysis criteria which might affect the findings.
- The expected relationship between traffic and rut progression was found, with the more heavily-trafficked roads displaying lower average rut progression rates; therefore there is a higher portion of the road length in the lower rut progression bands. Roads carrying higher traffic are built to higher design standard.
- The above observation holds true for link categories, with MI also showing a lower rate of deterioration and a higher portion of the road length in lower rut progression ranges than other road link categories.
- For all traffic ranges, the higher Thornthwaite Moisture Index (TMI) values were generally associated with a larger portion of road length in the higher rutting progression bands. This observation also holds true at regional levels except for the Metro and the Pilbara regions.

Task 2 involved the development of a rut progression model for WA which was an iterative process. The outputs from this modelling task are as follows:

- a total rutting progression model for the full MRWA network (Equation 9)
- refined total rutting progression models for each MRWA road link category (Equations 10, 11, 12 and 13).

Models were developed using the full network MRWA data which contained pavement strength, traffic, pavement age, etc. data and their combinations as observed in WA. However, these models did not contain the whole possible spectrum of independent variables, such as different traffic ranges and pavement strength levels. Around 66% of the analysed data samples had a deflection less than 600 micron. A vast majority of these samples also sat within a low traffic range of annual ESAs less than 1 million. Only 7% of the analysed sample had deflection greater than 1,000 microns. There were hardly any samples with a high/moderate combination of deflection (> 1,200 micron) carrying moderate/high traffic (> 1.5 ESA). Therefore, the model should only be applied within the conditions it was developed and should not be extended for the conditions such as:

- pavements with low strength carrying moderate to high traffic (no samples of this combination)
- pavements with moderate strength carrying moderate to high traffic (low to no samples of this combination).

Based on the developed network-level rutting model of Equation 9, Task 3 of the project involved testing and validation of the developed models against observed deterioration. This was done in 2 steps using datasets used in the model development as well as an independent dataset not used during model development. Differences were observed between collected and predicted rutting values using both datasets. This is expected as the predictive power of the network-level rutting model is moderate (adjusted $r^2 = 0.46$).

Under Task 4, the incremental model of Equation 14 predicted the rate of change in rutting based using the newly developed total rutting model of Equation 9 for 2 WA regions. These predictions were compared against the rate of change from the observed data. For all the years compared, the predicted rutting across different progression bands using the developed model were closer to the actual observed data.

As a part of this project, the following additional developments are also proposed for MRWA's consideration:

- further refinement of the developed model(s) to address significant changes in heavy vehicle loading and pavement conditions building on the outcome of a parallel Austroads project AAM6214 (Austroads 2023)
- development of models for other road deterioration parameters – e.g., a roughness model to provide a full suite of improved WA specific models.

6.2 Anticipated Benefit from the Developed Model

Implementation of the new model in MRWA dTIMS PMS tool is required to determine the differences of predictive capability of the models across MRWA road network. A strategic network analysis in dTIMS is also required to quantify the benefits from the use of the developed model. The anticipated benefits from using the developed rut model are as follows:

- overall lowering of the total transport cost due to targeted intervention
- lowering of the risk by increasing the accuracy in rutting prediction.

6.3 Directions for Future Work

As a part of this project, the following additional developments are also proposed for MRWA's consideration:

- Further refinement of the developed model(s) to address significant changes in heavy vehicle loading and pavement conditions building on the outcome of a parallel Austroads project AAM6214 (Austroads 2023). This could also address the development of a WA based deflection D0(t) model with time that could be used in combination with the total rutting progression model.
- Development of models for other road deterioration parameters – e.g., a roughness progression model to provide a full suite of improved WA specific models.

References

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Paterson, WDO 1987, *Road deterioration and maintenance effects: models for planning and management*, Highway design and maintenance standards series, Johns Hopkins University Press, Baltimore, USA.

Appendix A Task 2 Model Development – Models not Selected

A.1 Iteration 1

A.1.1 Iteration 1 – Data for Analysis

Data preparation

Data processing for this analysis utilised the same approach as described under Task 1 in Section 2.3. Additional processing steps involved the following:

- Using around 154,000 road segments in Section 2.3, the cumulative rutting data for each year were used as a data point after subtracting the initial densification rut (R0) from the total rutting values (as surveyed) at that point. The cumulative rutting at a given time, t, was expressed as (Rut (t) – R0).
- The corresponding pavement age was calculated for each data point using pavement year and data collection year.
- The traffic, ESAs (assuming ESA/HV = 2 or urban and 2.5 for Rural, No. of lane = 2) was calculated for a data point in each year as follows (Equation A1):

$$ESA(t) = AADT(t) * Percent\ HV * 365 * 0.5 * ESA/HV \quad \text{A1}$$

- From ESA(t), design capacity of the pavement was calculated as follows (Equation A2):

$$ESA0\ (at\ age\ zero) = ESA(t)/\ ((1 + traffic\ growth\ rate)^{\wedge}Pavement\ Age) \quad \text{A2}$$

where

CAP = $ESAo\ * CGF$

CGF = traffic growth rate

- The modified structural number at construction, SNC0 was then calculated using SNC-Capacity relationship (Equation A3) (Martin & Choummanivong 2018).

$$SNC0 = 1.128 * (CAP)^{\wedge}0.1033 \quad \text{A3}$$

- Initial rut densification (R0) for each road section was calculated using the HDM-4 formula (Equation A4) (Morosiuk et al. 2001).

$$R0 = 1 * 51740 * (ESAo^{\wedge}(0.09 + 0.0384 * 6.5 * SNCo - 1.6)) * (SNCo^{\wedge}(-0.502)) * (100^{\wedge}(-2.3)) \quad \text{A4}$$

- The deflection D0, in terms of the Benkelman Beam at the time of construction, was calculated from SNCo and converted to equivalent TSD deflection (Paterson 1987). It should be noted that this iteration did not use in-service TSD deflection from supplied data.

$$SNCo = 3.2 * D0\ (BB)^{\wedge}(-.63) \quad \text{A5}$$

$$D0\ (TSD) = \ 0.85 * D0\ (BB) + 0.056$$

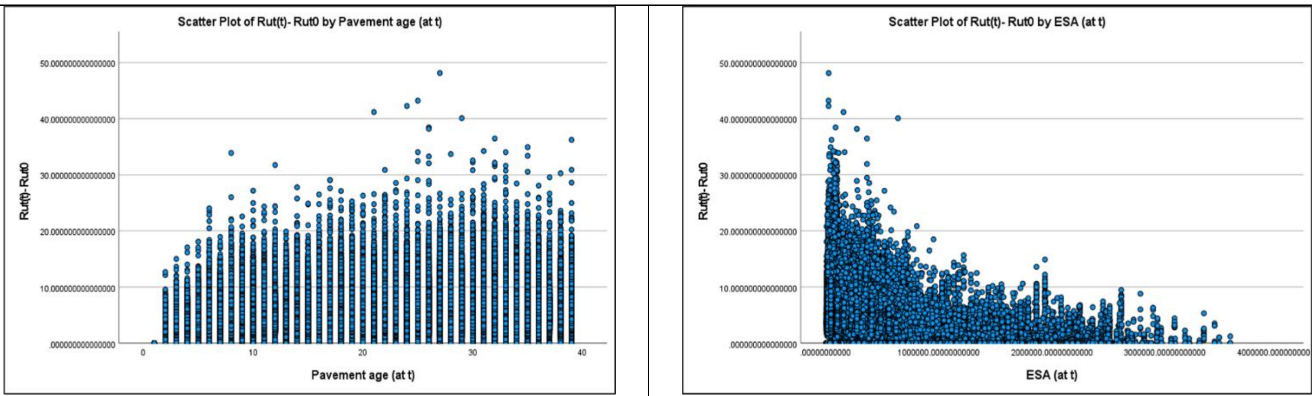
- Cumulative Rutting (Rut (t)- R0) was assumed to be zero at Pavement age = 1.
- Data points with pavement ages more than 40 years were discarded.

The above approach resulted in approximately 534,000 data samples for analysis.

Review of the data input

Initial exploration of the relationship between the dependent variable and some independent parameters (Pavement age and ESA) were conducted using scatter plots. Figure A.1 presents the respective plots. A higher pavement age was found to be associated with higher cumulative rutting although the trend was not very pronounced. The plot of Rut(t) – R0 vs ESA(t) reveals that the higher the input ESA, the lower the cumulative rutting. Hence, if this approach was adopted for the model development, the ESA would be expected have a negative coefficient in prediction of cumulative rutting.

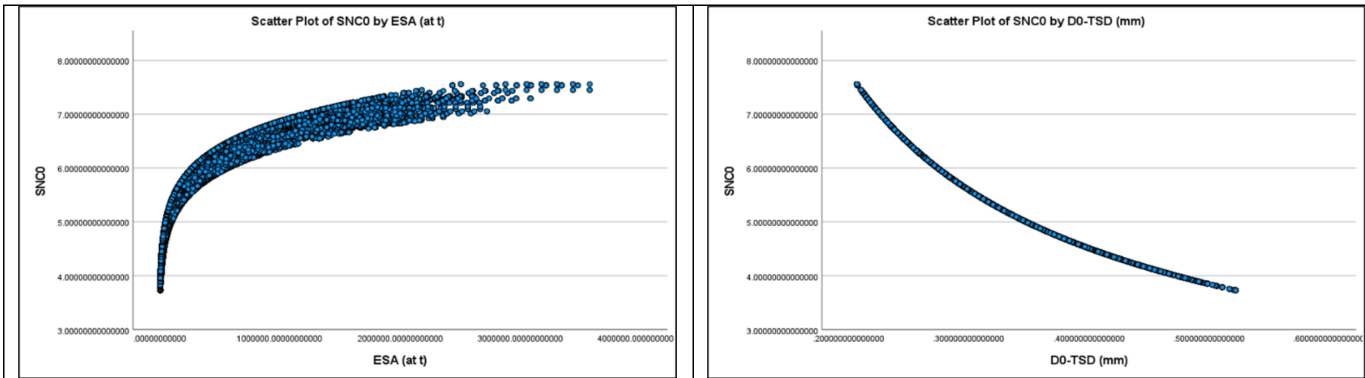
Figure A.1: Scatter plots- (a) cumulative rutting vs pavement age, (b) cumulative rutting vs ESA



(a) (b)

Since, both these strength and deflection values were calculated based on traffic, the association between these calculated variables and traffic were also explored. Figure A.2 presents the scatter plot of SNC0 vs ESA and SNC0 vs deflection at the time of construction. The higher the input ESA (at t), the higher is the calculated SNC0 as the pavement is designed to carry the traffic. This strong correlation is expected since SNC0 was calculated from cumulative ESA (CESA) and CESA was calculated from the current ESA and pavement age. This also implies that the calculated SNC0 and ESA cannot be used together in the model development. There was also a strong correlation between SNC0 and D0 at the time of construction as the latter was calculated from SNC0. Hence only one of these parameters can be used in the model development.

Figure A.2: Scatter plots – (a) SNC0 vs ESA (b) SNC0 vs deflection



(a) (b)

Correlation between cumulative rutting and other independent variables are included in Figure A.3.

Figure A.3: Correlation between dependent and independent variables

Correlations

		Rut(t)- Rut0	D0-TSD (mm)	ESA (at t)	Pavement age (at t)	Cumulative Rutting (at t)	TMI	Percent_Clay	SNC0
Rut(t)- Rut0	Pearson Correlation	1	-.033**	-.033**	.670**	.993**	.002	.043**	.001
	Sig. (2-tailed)		<.001	<.001	.000	.000	.074	<.001	.441
	N	534383	534383	534383	534383	534383	534383	534383	534383
D0-TSD (mm)	Pearson Correlation	-.033**	1	-.652**	.014**	-.092**	-.251**	.113**	-.979**
	Sig. (2-tailed)	<.001		.000	<.001	.000	.000	.000	.000
	N	534383	534383	534383	534383	534383	534383	534383	534383
ESA (at t)	Pearson Correlation	-.033**	-.652**	1	.078**	.069**	.285**	-.180**	.770**
	Sig. (2-tailed)	<.001	.000		.000	.000	.000	.000	.000
	N	534383	534383	534383	534383	534383	534383	534383	534383
Pavement age (at t)	Pearson Correlation	.670**	.014**	.078**	1	.674**	-.063**	-.021**	-.022**
	Sig. (2-tailed)	.000	<.001	.000		.000	.000	<.001	<.001
	N	534383	534383	534383	534383	534383	534383	534383	534383
Cumulative Rutting (at t)	Pearson Correlation	.993**	-.092**	.069**	.674**	1	.033**	.025**	.073**
	Sig. (2-tailed)	.000	.000	.000	.000		<.001	<.001	.000
	N	534383	534383	534383	534383	534383	534383	534383	534383
TMI	Pearson Correlation	.002	-.251**	.285**	-.063**	.033**	1	-.349**	.292**
	Sig. (2-tailed)	.074	.000	.000	.000	<.001		.000	.000
	N	534383	534383	534383	534383	534383	534383	534383	534383
Percent_Clay	Pearson Correlation	.043**	.113**	-.180**	-.021**	.025**	-.349**	1	-.136**
	Sig. (2-tailed)	<.001	.000	.000	<.001	<.001	.000		.000
	N	534383	534383	534383	534383	534383	534383	534383	534383
SNC0	Pearson Correlation	.001	-.979**	.770**	-.022**	.073**	.292**	-.136**	1
	Sig. (2-tailed)	.441	.000	.000	<.001	.000	.000	.000	
	N	534383	534383	534383	534383	534383	534383	534383	534383

**. Correlation is significant at the 0.01 level (2-tailed).

A.1.2 Iteration 1 – Analysis in SPSS

Using prepared data samples, Iteration 1 in the SPSS analysis involved testing both linear and nonlinear regressions in SPSS.

Linear regression

Linear regression was attempted first with different combinations of independent variables to observe the predictive power of the variables in cumulative rut progression. The following independent parameters were used (in different combinations):

- Pavement age (at t), Pavementageatt)
- ESA (at age zero and age t), ESAatt
- Climate, TMI
- Per cent Clay, Percent_Clay
- Calculated Deflection (at age zero), D0-TSD
- Calculated modified structural number (at zero age), SNC0, based on D0-TSD
- Rainfall.

A sample output is presented in Figure A.4.

Figure A.4: Iteration 1 – sample output – Linear regression in SPSS

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	D0-TSD (mm), Pavement age (at t), Percent_Clay, TMI, ESA (at age zero)[b]	.	Enter

a. Dependent Variable: Rut(t)- Rut0

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.688[a]	.474	.474	2.434828510

a. Predictors: (Constant), D0-TSD (mm), Pavement age (at t), Percent_Clay, TMI, ESA (at age zero)

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	4.255	.033		129.088	.000
	Pavement age (at t)	.172	.000	.672	674.427	.000
	ESA (at age zero)	-3.242E-6	.000	-.170	-127.952	.000
	TMI	.012	.000	.083	75.793	.000
	Percent_Clay	.029	.000	.073	68.204	.000
	D0-TSD (mm)	-9.192	.086	-.140	-106.791	.000

a. Dependent Variable: Rut(t)- Rut0

Figure A.4 shows that both ESA and D0-TSD have negative coefficients which are not expected from a mechanistic viewpoint. Also, the goodness of fit (adjusted r^2) is not very good (0.47).

A curve fitting technique was used in SPSS to determine the relationship between cumulative rutting and pavement age. A logarithmic relationship between Rut(t)- R0 and pavement age yielded better r^2 values than linear equation (Figure A.5). Hence logarithm of pavement age on a nonlinear equation was subsequently tested.

Figure A.5: Curve fitting in SPSS- Rut(t)- R0 vs Pavement age (at t)

Model Summary and Parameter Estimates

Dependent Variable: Rut(t)- Rut0

Equation	Model Summary R Square	F	df1	df2	Sig.	Parameter Estimates Constant	b1	b2
Linear	.448	434302.494	1	534381	.000	.986	.171	
Logarithmic	.563	689349.240	1	534381	.000	.173	1.729	
Quadratic	.536	308729.887	2	534380	.000	-.047	.441	-.008
Power[a]	.	.	.	.	.	.	.	
Exponential[a]	.	.	.	.	.	.	.	

The independent variable is Pavement age (at t).

a. The dependent variable (Rut(t)- Rut0) contains non-positive values. The minimum value is .000000000000000. Log transform cannot be applied. The Compound, Power, S, Growth, Exponential, and Logistic models cannot be calculated for this variable.

Non-linear regression

Different forms of non-linear regression equations were tested. The most promising equations were as follows in Equations A7 to A13:

$$Rut(t)\text{-}R0 = a*LN(Pavementageatt) \qquad A7$$

$$Rut(t)\text{-}R0 = a*LN(Pavementageatt) + b*(TMI + 100) + c*Percent\_Clay \qquad A8$$

$$Rut(t)\text{-}R0 = a*LN(Pavementageatt)*(b*(TMI + 100) + c*Percent\_Clay+d*D0\text{-}TSD) \qquad A9$$

$$Rut(t)\text{-}R0 = a*LN(Pavementageatt)+b*(1/SNC0) + c*TMI + d*Percent\_Clay \qquad A10$$

$$Rut(t)-R0 = a*LN(Pavementageatt) + b*(D0-TSD) + c*TMI + d*Percent\_Clay \quad A11$$

$$Rut(t)-R0 = a*LN(Pavementageatt) + b*(1/SNC0) + c*TMI + d*Percent\_Clay + e*ESAatt \quad A12$$

$$Rut (t)-R0 = a*LN(Pavementageatt) + b*(D0-TSD) + c*TMI + d*Percent\_Clay \quad A13$$

Sample SPSS outputs for Equation A13 are included in Figure A.6.

Figure A.6: Iteration 1 – output non-linear regression – Equation A13

Parameter Estimates

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
a	1.788	.002	1.784	1.792
b	.113	.020	.074	.153
c	.012	.000	.011	.012
d	.019	.000	.019	.020

ANOVA[a]

Source	Sum of Squares	df	Mean Squares
Regression	12338514.95	4	3084628.738
Residual	2505283.410	534379	4.688
Uncorrected Total	14843798.36	534383	
Corrected Total	6080766.332	534382	

Dependent variable: Cumulative Rutting (at t)

a. R squared = 1 - (Residual Sum of Squares) / (Corrected Sum of Squares) = .588.

A.2 Iteration 2

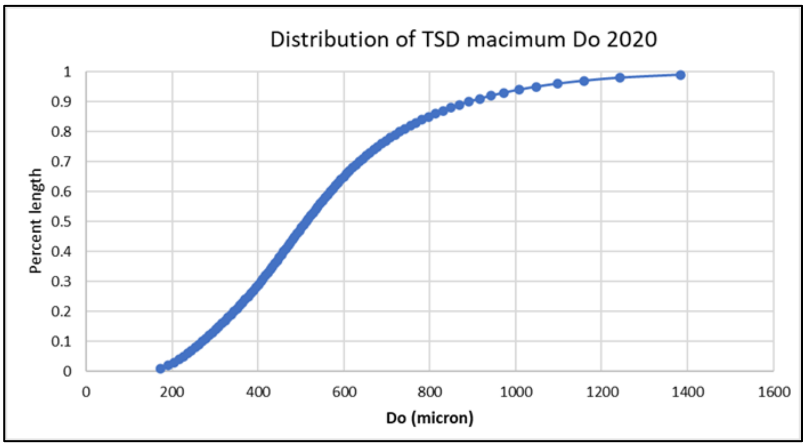
A.2.1 Iteration 2 – Data for Analysis

Data processing for iteration 2 involved the same approach as described in Section 2.3. The rate of rutting progression, $\Delta rut(ti)/\Delta ti$, estimated during Task 1 was used a dependent variable. In addition, deflection data (as maximum D0) was extracted from TSD 2018 and 2020 data unlike calculating it from design capacity and initial strength as in Iteration 1.

Estimation of deflection

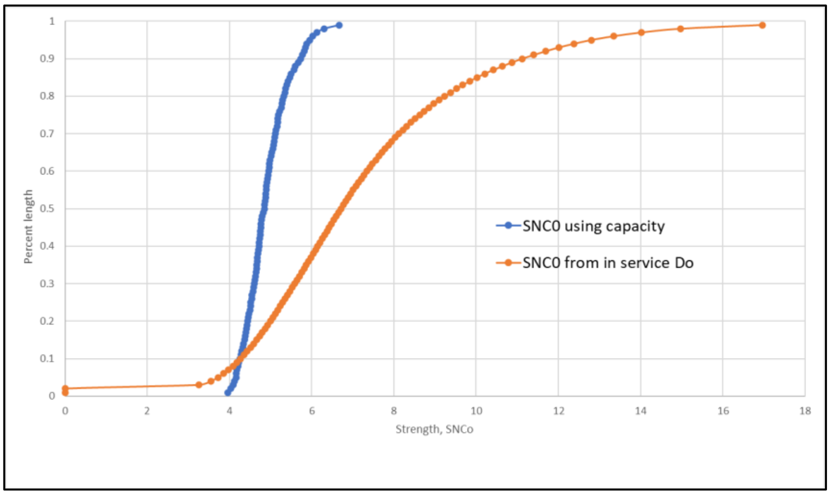
Maximum D0 information was extracted from TSD 2018 and 2020 data. The network displayed relatively low deflection with 65% of the network having maximum deflection < 600 microns in TSD 2020 data (Figure A.7). Also, changes in road segment-specific deflection over 2 years were found to be relatively small for most of the network (66% of the network had a deflection increase of ±100 micron over 2-year period).

Figure A.7: Distribution of maximum TSD deflection (D0) in 2020



A comparison of strength, SNC0, calculated from average maximum deflection, D0av, using TSD data from 2018 and 2020, and the same, SNC0, calculated using design capacity during Iteration 1 was plotted in Figure A.8. A more realistic and wider distribution of strength is observed for the TSD based deflection data. In subsequent analyses the D0av was used to account for pavement strength.

Figure A.8: Strength (SNC0) distribution comparison- calculated using TSD deflection vs estimated using design capacity



A.2.2 Iteration 2 – Analysis in SPSS

Non-linear regression

Different non-linear equation forms using rate of change of rutting as an independent variable were tested. The most promising format was as follows (Equation A14):

$$\text{Rate of change of rutting } \Delta rut(ti)/\Delta ti = a1*D0av + a3*(TMI + 100) + a4*(Percent\_Clay) - a5*(AGEi - 1) \qquad A14$$

The corresponding SPSS outputs are presented in Figure A.9.

Figure A.9: Iteration 2- output – non-linear regression

Parameter Estimates

Parameter	Estimate	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
a1	.265	.008	.249	.281
a3	.004	.000	.004	.004
a4	-3.659E-6	.000	.000	.000
a5	.003	.000	.003	.003

ANOVA[a]

Source	Sum of Squares	df	Mean Squares
Regression	17544.781	4	4386.195
Residual	12276.228	61021	.201
Uncorrected Total	29821.008	61025	
Corrected Total	12547.138	61024	

Dependent variable: ruttingprogression[a]

a. R squared = 1 - (Residual Sum of Squares) / (Corrected Sum of Squares) = .022.

A.3 Iteration 3

A.3.1 Iteration 3 – Data for Analysis

The data used for Iteration 3 was mostly same as described in Iteration 1. The only parameter modified during Iteration 3 was the use of in-service TSD deflection data (as outlined in Section A.2) instead of using the calculated deflection from design capacity.

A.3.2 Iteration 3 – Analysis in SPSS

Various equation formats of non-linear regression were tested to predict cumulative rutting (Rut(t)- R0) as a function of independent variables while maintaining the boundary condition. The equations tested are as follows (Equations A15 to A20):

Cumulative rutting (t) = a1*((Pavementageatt-1)^a2)*(a3*(100 + TMI)*D0-TSDav + a4*ESAatt*Percent_Clay) A15

Cumulative rutting (t) = a1*(Pavementageatt-1)*(a2*(100 + TMI) + a3*D0-TSDv+ a4*ESAatt + a5*Percent_Clay) A16

Cumulative rutting (t) = a1*(Pavementageatt-1)^a2 A17

Cumulative rutting(t) = a1*((Pavementageatt-1)^a2)*(a3*D0-TSDav + a5*Percent_Clay) A18

Cumulative rutting (t) = a1*((Pavementageatt-1)^a2)*(a3*D0-TSDav) A19

Cumulative rutting (t) = a1*(Pavementageatt-1)*(a2*(D0-TSDav) + a3*TMI + a4*Percent_Clay) A20

Sample SPSS outputs using Equation A17 is presented in Figure A.10.

Figure A.10: Iteration 3 – output Equation A17 – non-linear regression

Parameter Estimates

Parameter	Estimate	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
a1	3.208	.014	3.180	3.236
a2	.178	.001	.176	.181

ANOVA[a]

Source	Sum of Squares	df	Mean Squares
Regression	10022916.02	5	2004583.203
Residual	2229779.514	459562	4.852
Uncorrected Total	12252695.53	459567	
Corrected Total	5244112.987	459566	

Dependent variable: Rut(t)- Rut0[a]

a. R squared = 1 - (Residual Sum of Squares) / (Corrected Sum of Squares) = .575.

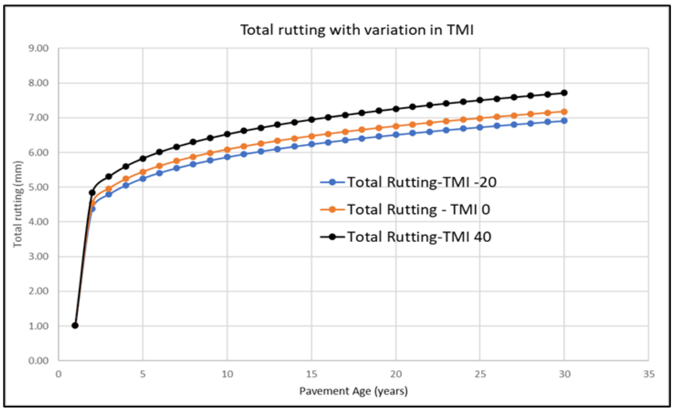
A.4 Iteration 4

A.4.1 Plotting of the Iteration 4 Rutting Model and Comparison Against Austroads Model

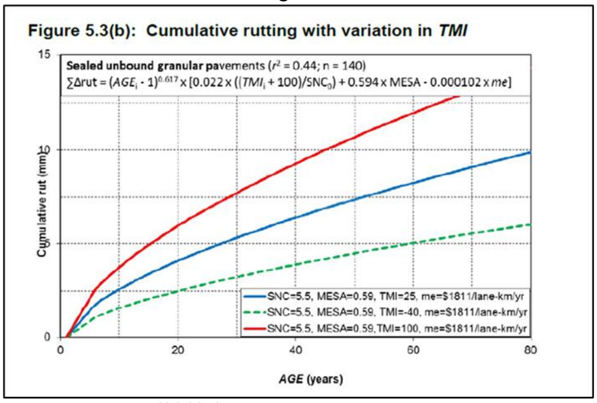
Selected modelling equation was plotted by varying age, climate and deflection and compared against the Austroads model (Austroads 2010).

Figure A.11: Plotting of Total rutting (using selected equation) by varying TMI (deflection = 800 micron) and comparison with Austroads cumulative rut model

Total rutting (t)= 1.023+1.525*((Pavementageatt-1)^0.167)*(1+AverageDo*0.001+(100+TMI)*0.005)

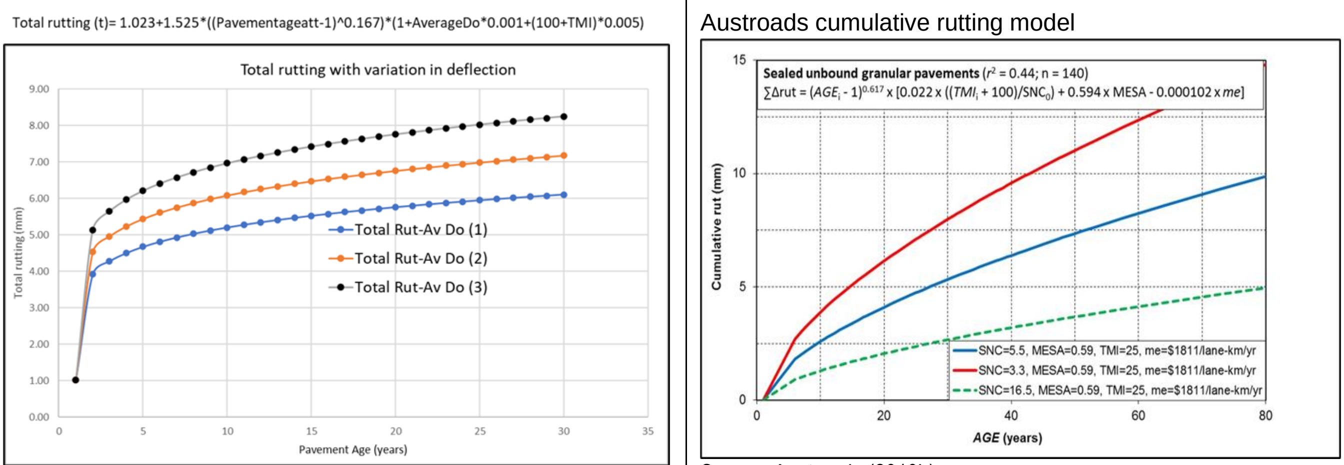


Austroads cumulative rutting model



Source: Austroads (2010b).

Figure A.12: Plotting of total rutting (using selected equation) by varying deflection (TMI = 0) and comparison with Austroads cumulative rut model



Source: Austroads (2010b).

Figure A.11 and Figure A.12 show that:

- The developed total rutting model is sensitive to the changes in climate as well as deflection (strength).
- A sharp rise in total rutting is observed from years 1 to 3. This is due to lack of rutting data for new pavements.
- A reduction of rut progression at higher ages is observed similar to Austroads (although the developed model is much flatter confirming relatively stronger pavements of WA).

A.4.2 Total Rutting Model for MRWA Link Categories

The selected model, Equation 3 (Section 3.7.2), was also tested in SPSS modelling analyses by separating samples for each MRWA link category to explore if the significance of the parameters as well as modelling regression coefficient changes or not for different road link categories. Table A.1 outlines the SPSS sample sizes for 4 MRWA link categories.

Table A.1: SPSS samples under each road link

Link category	No of samples
AW (includes AW and AW+ road links)	74,530
BW (includes BW and BW+ road links)	188,673
CW	75,189
MI (includes MI and MFF road links)	33,360

SPSS outputs for AW, BW and CW using the selected equation are presented in Figure A.13. Small changes in the coefficient values are observed for each link categories though not very significant except for a5 (coefficient for TMI) for the CW link category. Improvement in modelling predictions (adjusted r^2 values) are also attained for all 3 link categories compared to the full sample result. CW link category has the highest adjusted r^2 values among the 3 link categories.

Figure A.13: SPSS outputs using selected equation for link category AW BW and CW

Parameter Estimates

Parameter	Estimate	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
a1	.998	.014	.970	1.025
a2	1.539	.038	1.465	1.613
a3	.124	.004	.117	.131
a4	.001	.000	.001	.001
a5	.009	.000	.009	.010

ANOVA[a]

Source	Sum of Squares	df	Mean Squares
Regression	1754426.773	5	350885.355
Residual	338003.500	69906	4.835
Uncorrected Total	2092430.273	69911	
Corrected Total	783198.884	69910	

Dependent variable: Total Rutting (at t)[a]

a. R squared = 1 - (Residual Sum of Squares) / (Corrected Sum of Squares) = .568.

(a) AW

Parameter Estimates

Parameter	Estimate	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
a1	.999	.008	.982	1.015
a2	1.388	.021	1.347	1.428
a3	.199	.002	.194	.204
a4	.001	.000	.001	.001
a5	.006	.000	.005	.006

ANOVA[a]

Source	Sum of Squares	df	Mean Squares
Regression	4065360.512	5	813072.102
Residual	750493.886	172865	4.342
Uncorrected Total	4815854.399	172870	
Corrected Total	1816839.241	172869	

Dependent variable: Total Rutting (at t)[a]

a. R squared = 1 - (Residual Sum of Squares) / (Corrected Sum of Squares) = .587.

(b) BW

Parameter Estimates

Parameter	Estimate	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
a1	.997	.014	.971	1.024
a2	.900	.044	.814	.986
a3	.174	.005	.165	.184
a4	.001	.000	.001	.001
a5	.020	.002	.017	.023

ANOVA[a]

Source	Sum of Squares	df	Mean Squares
Regression	1006671.336	5	201334.267
Residual	158581.087	49307	3.216
Uncorrected Total	1165252.422	49312	
Corrected Total	407258.007	49311	

Dependent variable: Total Rutting (at t)[a]

a. R squared = 1 - (Residual Sum of Squares) / (Corrected Sum of Squares) = .611.

(c) CW

The modelling equations for total rutting for AW, BW and CW are as follows (Equations A21 to A23):

Link category AW: A21

$$\text{Total rutting at t} = 0.99 + 1.539 * ((\text{Pavementageatt} - 1)\text{^}0.124) * (1 + \text{D0av} * 0.001 + (100 + \text{TMI}) * 0.009)$$

Link category BW: A22

$$\text{Total rutting at t} = 0.99 + 1.388 * ((\text{Pavementageatt} - 1)\text{^}0.199) * (1 + \text{D0av} * 0.001 + (100 + \text{TMI}) * 0.006)$$

Link category CW: A23

$$\text{Total rutting at t} = 0.99 + 0.900 * ((\text{Pavementageatt} - 1)\text{^}0.174) * (1 + \text{D0av} * 0.001 + (100 + \text{TMI}) * 0.020)$$

However, link category MI (including MFF) produced an unsatisfactory output for the selected modelling equation (Equation 3) with negative coefficients for all parameters. MI is the link category with the highest design standards (relatively high strength than rest of the link categories) and less susceptible to climate variation. Hence Equation 1 in Section 3.7.2 was tested on this sample to explore if the pavement age on its own is a significant parameter or not. The SPSS output using Equation 1 showed pavement age was statistically significant although the predictive power of the model is lower than the same achieved for the full sample (adjusted r^2 =0.425).

SPSS outputs for MI using both equations are presented in Figure A.14.

Figure A.14: SPSS outputs using selected equation for link category MI

Equation format 3

Parameter Estimates

Parameter	Estimate	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
a1	1.001	.024	.954	1.049
a2	-.156	.092	-.337	.026
a3	.030	.006	.019	.041
a4	-.032	.019	-.069	.004
a5	-.118	.067	-.250	.013

ANOVA[a]

Source	Sum of Squares	df	Mean Squares
Regression	652926.075	5	130585.215
Residual	157601.956	29846	5.281
Uncorrected Total	810528.031	29851	
Corrected Total	301513.964	29850	

Dependent variable: Total Rutting (at t)[a]

a. R squared = 1 - (Residual Sum of Squares) / (Corrected Sum of Squares) = .477.

Equation format 1

ANOVA[a]

Source	Sum of Squares	df	Mean Squares
Regression	679327.389	3	226442.463
Residual	185375.995	33356	5.558
Uncorrected Total	864703.383	33359	
Corrected Total	322407.257	33358	

Dependent variable: Total Rutting (at t)[a]

a. R squared = 1 - (Residual Sum of Squares) / (Corrected Sum of Squares) = .425.

Parameter Estimates

Parameter	Estimate	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
a1	.997	.023	.951	1.043
a2	3.270	.059	3.154	3.387
a3	.100	.006	.089	.111

Final modelling equation for Link category MI is as follows (Equation A24).

$$\text{Total rutting at t} = 0.99 + 3.270 * ((\text{Pavementageatt} - 1)\hat{}100) \quad \text{A24}$$

A.4.3 Total Rutting Model for MRWA Road Types

The current MRWA road types are based on link categories. MRWA previously used distinct road types named as ‘H’ and ‘M’. As requested by MRWA, the selected total rutting equation (Equation 3) was also tested in SPSS by separating samples for each of these 2 road types.

SPSS outputs for road types H and M are presented in Figure A.15.

Figure A.15: SPSS outputs using selected equation for road type H and M

(a) Road Type-H

Parameter Estimates

Parameter	Estimate	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
a1	1.028	.008	1.013	1.043
a2	1.455	.018	1.420	1.490
a3	.178	.002	.174	.182
a4	.001	.000	.001	.001
a5	.005	.000	.005	.005

ANOVA[a]

Source	Sum of Squares	df	Mean Squares
Regression	5749680.069	5	1149936.014
Residual	1124019.904	243200	4.622
Uncorrected Total	6873699.972	243205	
Corrected Total	2469440.878	243204	

Dependent variable: TotalRuttingatt

a. R squared = 1 - (Residual Sum of Squares) / (Corrected Sum of Squares) = .545.

(b) Road Type-M

Parameter Estimates

Parameter	Estimate	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
a1	1.011	.011	.990	1.032
a2	1.861	.035	1.793	1.928
a3	.118	.004	.112	.125
a4	.001	.000	.001	.001
a5	.006	.000	.005	.006

ANOVA[a]

Source	Sum of Squares	df	Mean Squares
Regression	1719679.759	5	343935.952
Residual	305388.029	78201	3.905
Uncorrected Total	2025067.788	78206	
Corrected Total	827784.627	78205	

Dependent variable: TotalRuttingatt

a. R squared = 1 - (Residual Sum of Squares) / (Corrected Sum of Squares) = .631.

Final modelling equations for total rutting are as follows (Equations A25 and A26):

Road Type H: A25

$$\text{Total rutting at t} = 1.03 + 1.455 * ((\text{Pavementageatt} - 1)\text{^}.178) * (1 + \text{D0av} * 0.001 + (100 + \text{TMI}) * 0.005)$$

Road Type M: A26

$$\text{Total rutting at t} = 1.01 + 1.861 * ((\text{Pavementageatt} - 1)\text{^}.118) * (1 + \text{D0av} * 0.001 + (100 + \text{TMI}) * 0.006)$$

Appendix B Task 3 – Testing and Validation of the Iteration 4 Model (Not Selected)

B.1 General

Task 3 involves desktop-based testing and validation of the developed rutting model against observed deterioration. A comparison was made between the predicted rutting value with the measured rutting value. The above was done using both the training dataset (dataset used in developing the rutting model) and the test dataset (dataset excluded from the rutting model development).

Earlier set of validation was done using total rutting model in Iteration 4 and the results are appended in Appendix A.2. This section includes updated testing and validation using final model (Iteration 5).

B.2 Testing and Validation Approach of the Rutting Model

The developed network-level rut model was tested and validated against the observed deterioration. Validation was conducted in 2 steps:

- Approach 1 – Using the training dataset
- Approach 2 – Using the test dataset.

B.2.1 Approach 1: Using the Training Dataset

Approach 1 involved testing using the dataset used to develop the total rutting model. Based on the selected network level equation 3, the validation steps involved the following:

- calculated (i.e. predicted) total rutting for each sample using the independent parameters for that sample (age, deflection, TMI)
- prepared scatter plot of observed (i.e., surveyed total rutting) vs predicted total rutting using all analysed samples (around 370,000 samples)
- prepared cumulative distributions of both observed and predicted total rutting
- calculated the absolute differences between observed and predicted rutting by the following:
  - differences in rutting values (mm)
  - differences relative to observed rutting (%)
- created ranges for the differences to determine analysed training dataset samples in different rutting ranges.

Figure B.1 and Figure B.2 display the scatter plot of observed vs predicted total rutting and cumulative distributions for both respectively. The scatter plot shows considerable spread between observed and predicted rutting. This is expected as the predictive power of the network-level rutting model is moderate (adjusted r^2 = 0.57). Cumulative distributions reveal 80% of the analysed sample have total rutting of around 6 mm from both observed and predicted rutting. However, some overprediction and underprediction (using the modelled equation) was observed for samples with rutting below and above 6 mm respectively.

Figure B.1: Observed vs predicted total rutting – training dataset

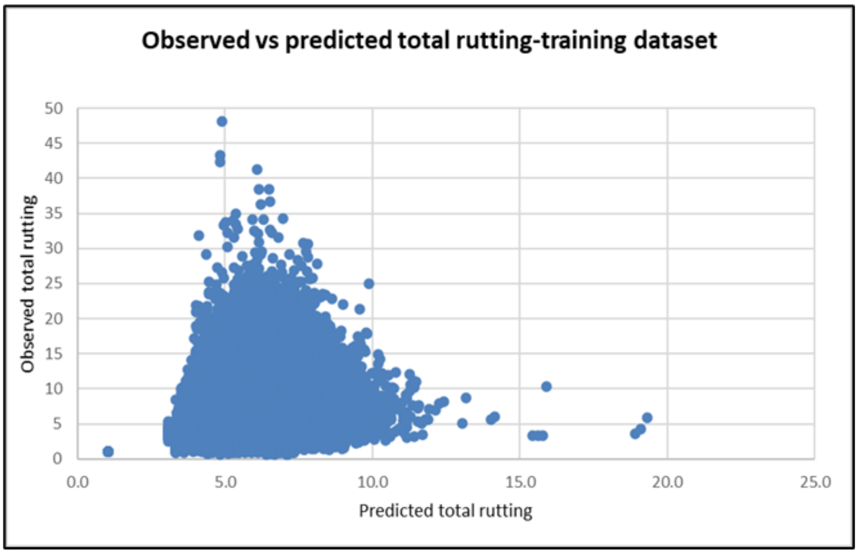


Figure B.2: Cumulative distribution plots – observed and predicted total rutting – training dataset

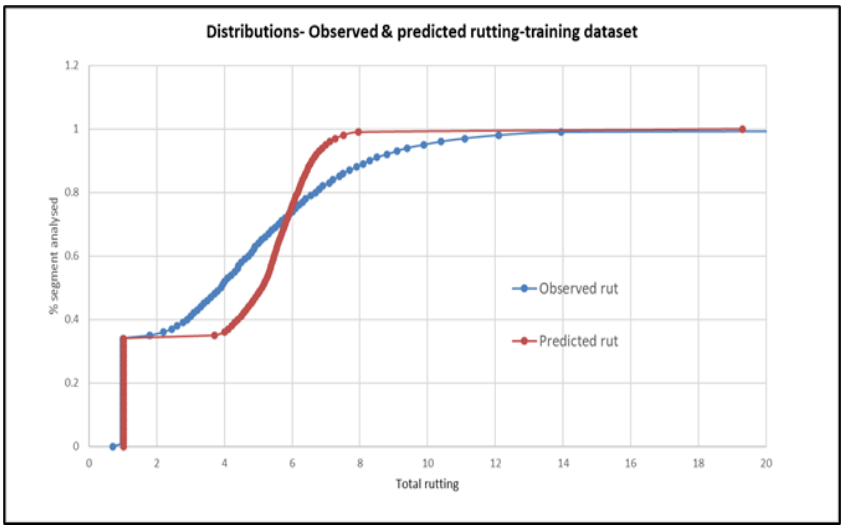


Figure B.3 and Figure B.4 display the differences (absolute as well as percentage respectively) between observed vs predicted total rutting using all analysed training dataset samples.

Figure B.3: Absolute differences between observed and predicted total rutting – training dataset

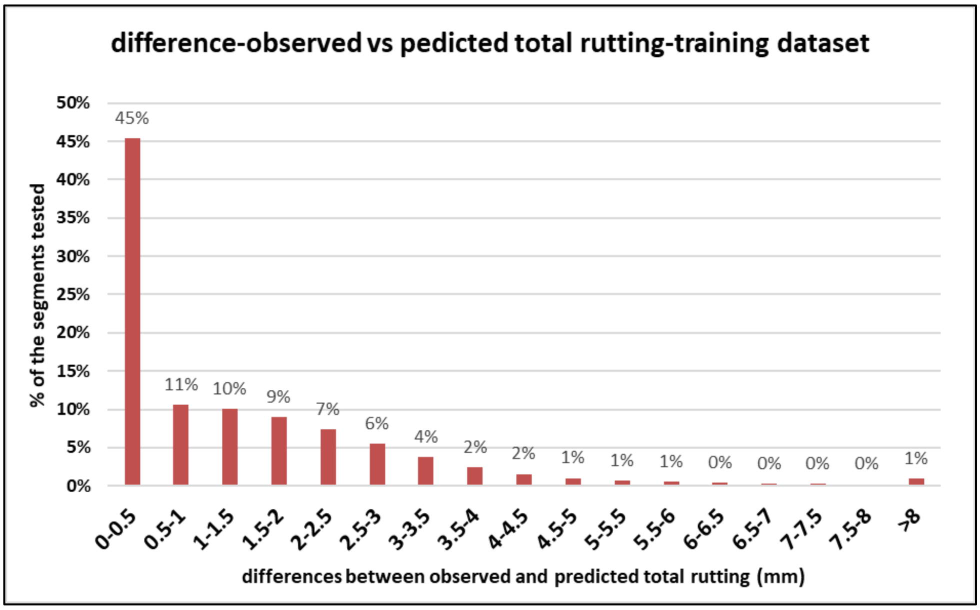


Figure B.4: Per cent Differences between observed and predicted total rutting – training dataset

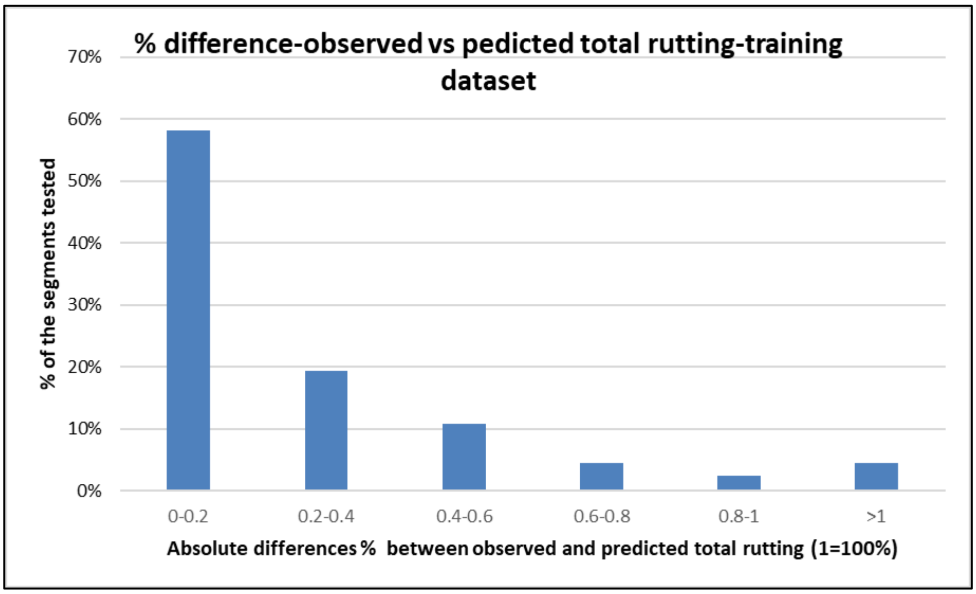


Figure B.3 shows that in terms of absolute rutting values, the differences between observed and predicted rutting were less than 0.5 mm for 45% of the samples. For 75% of the rutting samples, the differences between observed and predicted rutting were within 2 mm. For 1% of the rutting sample, the difference between observed and predicted rutting was more than 8 mm.

Figure B.4 shows that in terms of percentages, the difference between observed and predicted values was within 20% for 58% of the analysed samples. There were less than 5% of the samples where the differences were more than 100%.

B.2.2 Approach 2: Using the Test Dataset

Approach 2 of the testing involved working with the dataset discarded during model development process. Based on selected network level equation, the validation steps involved the following:

- From the discarded dataset in Section 3, segment samples where 2 consecutive years were free from maintenance affects were filtered out for testing and validation.
- Each data point from the above segments was used as a sample and the corresponding pavement age was calculated.
- Using the selected total rutting model, the calculated (i.e., predicted) total rutting for each sample was estimated using the independent parameters for that segment (age, deflection, TMI).
- Prepared a scatter plot of observed (i.e., surveyed total rutting) vs predicted total rutting using the samples (around 45,000 samples).
- Prepared a cumulative distribution of both observed and predicted total rutting.
- Calculated the absolute differences between observed and predicted rutting by the following:
  - differences in rutting values (mm)
  - differences relative to observed rutting (%).
- Created ranges for the differences to distribute the analysed test dataset samples into different rutting ranges.

Figure B.5 and Figure B.6 display the scatter plots of observed vs predicted total rutting and cumulative rutting distributions for both respectively, using the test data samples. The scatter plot shows considerable spread between observed and predicted rutting. This is expected as the predictive power of the network-level rutting model is moderate (adjusted r^2 = 0.57). In addition, as this comparison is based on the test data (data not used to develop the model), the accuracy is expected to be less than the training data.

The cumulative distribution shown in Figure 4.6 of observed data reveal 80% of the analysed samples have total rutting of around 10 mm. However, the model Equation 3 predicts the same estimating a total rutting of around 7 mm for 80% of the analysed test dataset samples.

Figure B.5: Observed vs predicted total rutting – test dataset

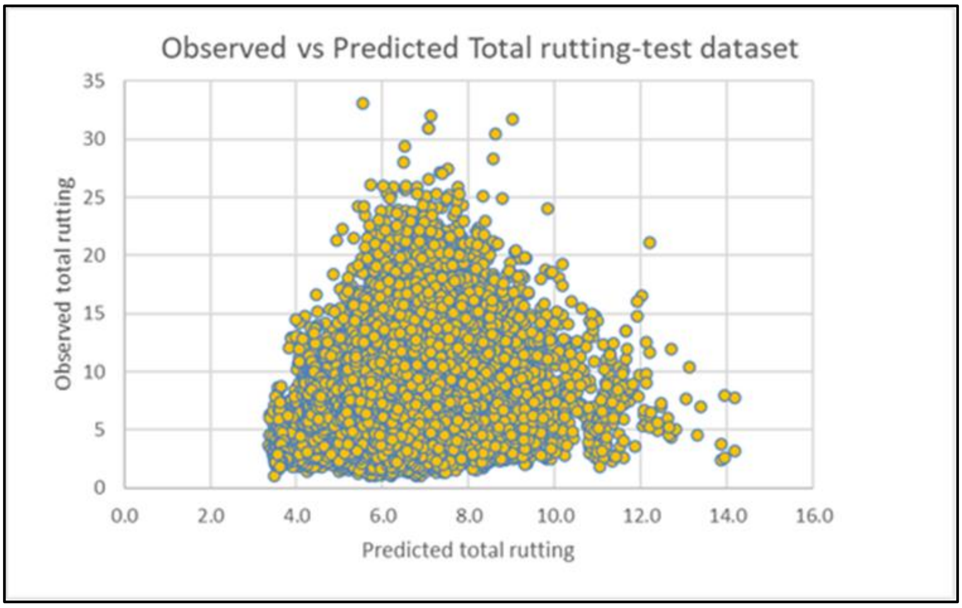


Figure B.6: Cumulative distribution plots – observed and predicted total rutting – test dataset

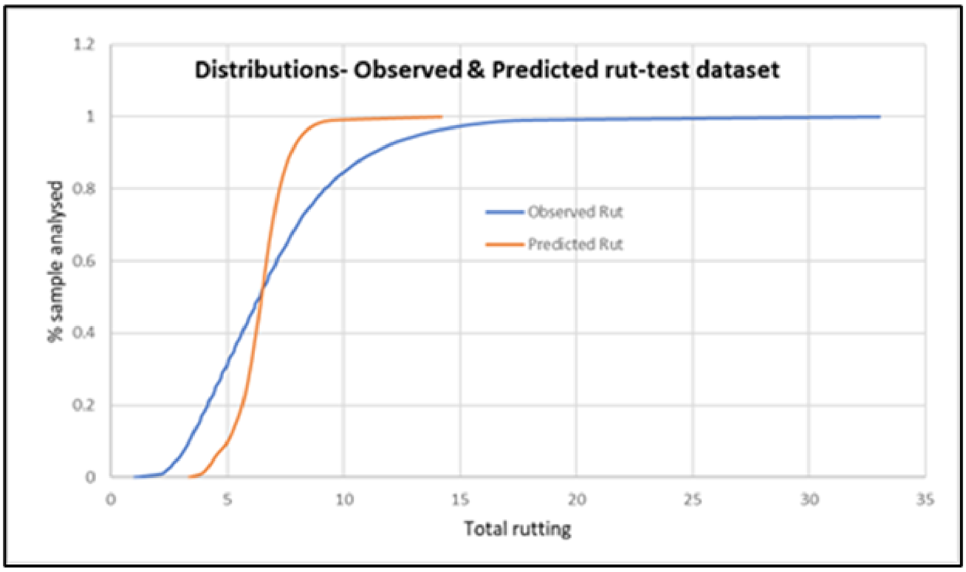


Figure B.7 and Figure B.8 display the differences (absolute values as well as percentage respectively) between observed vs predicted total rutting using analysed test dataset samples.

Figure B.7: Absolute differences between observed and predicted total rutting – test dataset

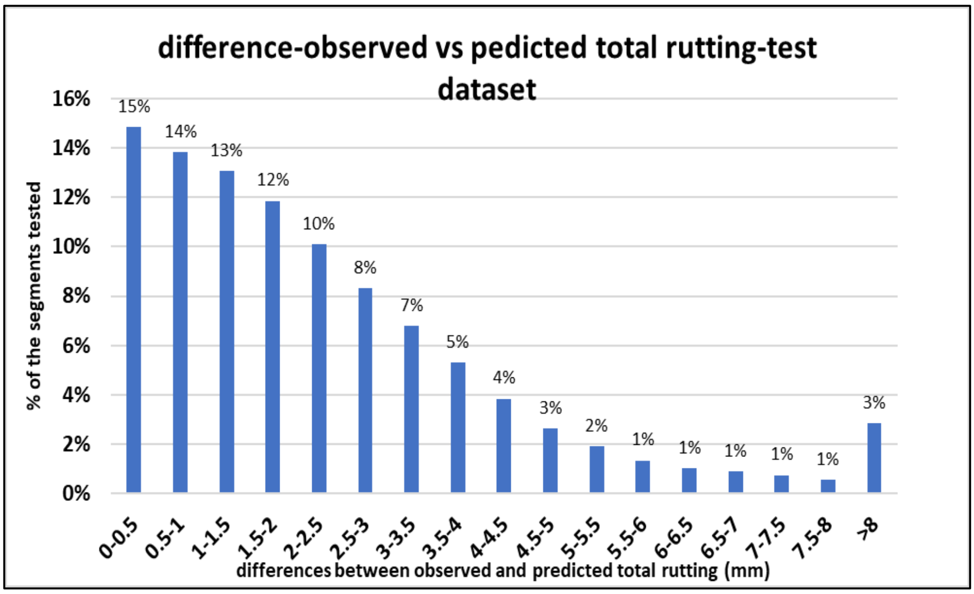
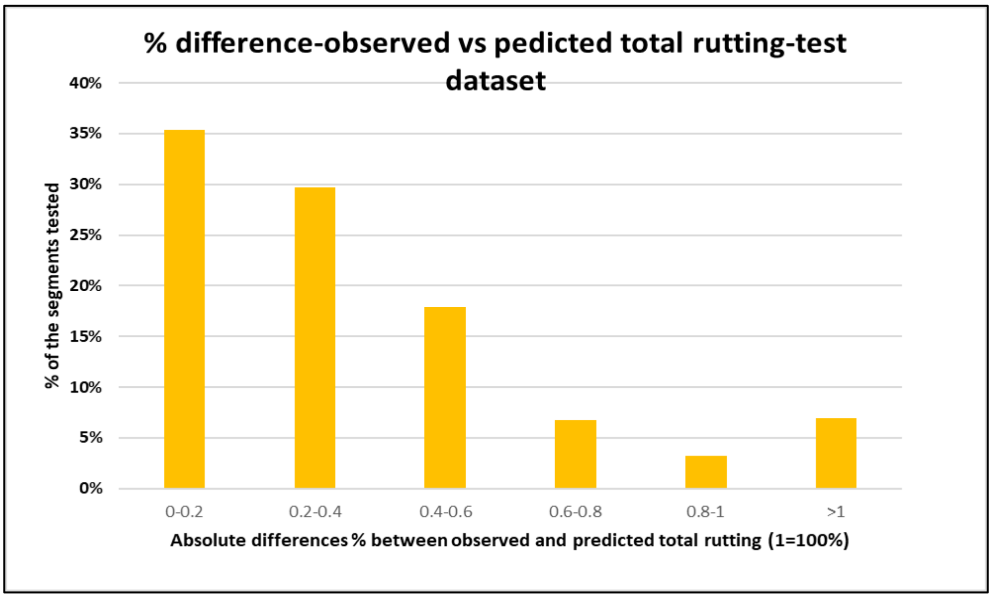


Figure B.8: Per cent differences between observed and predicted total rutting – test dataset



In terms of absolute values, the differences between observed and predicted rutting were less than 0.5 mm for only 15% of the samples, compared to 45% using the training data. For 54% of the samples, the difference between observed and predicted rutting was within 2 mm. Some 3% of samples displayed a difference between observed and predicted rutting of more than 8 mm. Since this comparison was based on the test data, the resulting accuracy was less than the training data.

In terms of percentages, for 35% of the analysed test dataset samples, the difference between observed and predicted values was within 20%. There were around 7% of the samples where the differences were more than 100%.

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