A case study of a new tool to identify good performing pavements in New Zealand

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Abstract

With the advancement of digital technology, the collection of pavement data has become commonplace. The improvement of tools to extract useful information from pavement databases has become a priority to justify expenditures. This paper presents a case study of PaveMD, a tool that integrates multi-dimensional data structures with a data-driven fuzzy approach to identify high performing pavement sections. Combining this tool with an innovative paradigm where the focus is on repeating success can bring additional value to existing pavement data. The case study shows that PaveMD can identify pavement sections that are performing well by comparing performance measures for the New Zealand context.

In this paper, PaveMD's development is described, and its implementation is showcased using data from the New Zealand Long-Term Pavement Performance (LTPP) database. It is recommended that this approach be further developed and extended to other types of infrastucture and databases internationally.

Highlights:

- Development of a new tool for pavement data analysis using a New Zealand case study.
- A novel approach to classify pavement sections using performance data.
- Use of a fuzzy multi-dimensional framework for pavement classification.

Keywords: Pavement data, Pavement selection, Repeating success, Multi-dimensional analysis, New Zealand, Chip-seal, Pavement performance.

1 Introduction

Transportation agencies have recognized an opportunity to extract additional information from their existing pavement databases. Like many agencies, Waka Kotahi, the New Zealand Transport Agency (NZTA) has been particularly interested in extracting more information from their Long-Term Pavement Performance (LTPP) program (NZTA, 2016). The classic approach for the analysis of pavement data tends to be a forensic one, where the analyst focuses on what went wrong to understand it and be able to find a potential solution to avoid future failures of the same nature. An alternative approach would focus on success. This approach seeks to identify the information necessary to replicate success rather than to try to avoid failure. It shifts the objective of the analysis from a design-centric approach to a construction-centric approach. Here, pavement success becomes a relative term, indicating the best performing pavement section in a specific context. This approach was first used by Gransberg, Senadheera, & Karaca (1998) on a statewide constructability review project for the Texas Department of Transportation (TxDOT). While the project did not use analytical tools, it did maintain the focus on pavement success. TxDOT later attributed its results to a savings of over $6 million in the first two years of its implementation. This study seeks to expand the fundamental approach of the TxDOT research to New Zealand pavement data and classify pavement sections based on their performance for further investigation.

The objectives of the paper are:

1. Investigate current and emerging methods from literature to analyze pavement performance data.
2. Develop a tool to classify pavement sections based on commonly available pavement performance data.

3. Showcase the tool using the New Zealand Long-Term Pavement Performance (LTPP) database as a case study and make further research recommendations.

The first part of this paper presents a review of pavement performance in a New Zealand context; the paper then discusses the tool's development, called PaveMD, the techniques used, information structure and implementation. PaveMD is then showcased using data from the New Zealand LTPP database. Finally, this paper presents a discussion, the limitations and recommendations for research moving forward.

2 Background

2.1 The distinction between pavement success and performance in New Zealand

In New Zealand, national roads are predominantly paved with chip-seal to remain cost-effective. These pavements consist of an unbound granular base surfaced with a type of chip-seal. In this context, the definition of pavement performance is relative, with many complex variables and confounders based on the context. For example, a pavement towards the end of its life may not be performing that well but may have carried twice the amount of heavy traffic in poor geotechnical and climate conditions and thus could be classified as more successful. Instead, here the focus will be on the performance of chip-seal pavements at the network level (Gransberg, Scheepbouwer & Tighe, 2010). This is typically measured using pavement performance measures such as rutting, roughness and texture with pavement load (ESALs) over time. These key performance measures have also been selected as the basis for the New Zealand Long Term Performance database (NZ LTPP). Other variables that impact performance, such as the amount of drainage, link significance, gradients and elevation are also important but are context-specific. These factors are typically assessed on a case-by-case basis, not at the network level. The new tool utilizes available pavement performance measures for New Zealand pavements listed above, but it can be extended to include other performance measures using a similar novel approach.

Following on, to gain an understanding of the existing research with relevance to PaveMD, this section contains the following three sub-sections:

- Review of data structures commonly used in transportation and pavement research
- Review of pavement data classifiers
- Review of data consolidation methods (Composite indices)

2.1 Review of data structures commonly used in transportation

Relational database management systems (RDBMS) or 'flat tables' have been used for many years. It is the basis upon which the most extensive pavement data sets are held. Recently it has been shown that classical statistical techniques have seen limited success with current pavement databases in New Zealand. Neaylon et al. (2017) proposed that New Zealand pavement data should be restructured to be more compatible with smart computing to extract meaningful results more affordably. Additionally, Colliat (1996) also pointed to the many limitations of this standard and suggested a move to a multi-dimensional framework (MDF). At this point, it is essential to note that other terminology and jargon exists with similar definitions. For example, the OLAP-Cube (online analytical processing) (Salley & Codd, 1998) is synonymous with MDF and Multi-dimensional analysis (MDA). This paper will use the more generalized terminology, MDF for the data structure, and MDA for the analysis of multi-dimensional data and framework.

An MDF is structured to answer queries about trends and patterns in data (Larson et al. 2011). Pavement data is well suited to MDF as data is typically collected in set intervals. In New Zealand, the SCRIM truck (Sideway-force Coefficient Routine Investigation Machine) collects information annually between October and March Each year (NZTA 2019). This allows “annual” dimensions to be added to a MDF. Figure 1 depicts the benefits that an MDF and MDA approach could bring to pavement data. MDF can provide a context-specific view when looking at data.

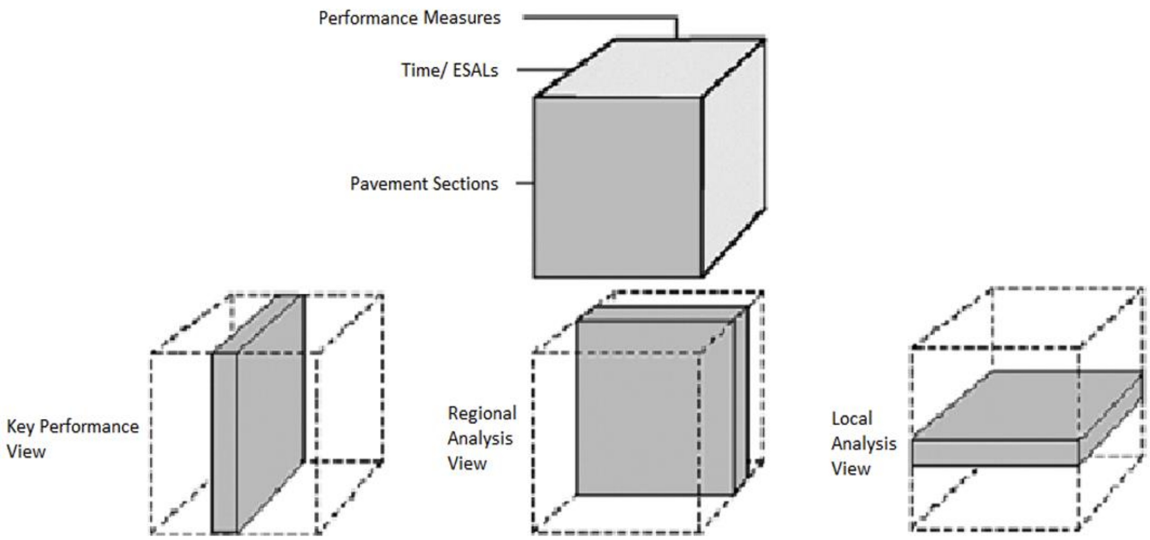

Figure 1: Visualization of multi-dimensional perspectives as it relates to different entities.

There are several benefits of moving to an MDF and MDA approach.

- The ability to provide a context-focused view when viewing the same structure.
- Transformation of a scheme into a more direct context-focused environment.
- Multi-dimensional data is implicitly joined, enabling fast queries.
- Relationships between different layers of information are easily identified.
- Matrix algebra can be applied for advanced query outputs. Sub-matrices can simply be obtained through matrix manipulation.

(Colliat 1996; Laker 2006; Park & Cai 2017)

The MDF approach has seen limited use in the transportation industry, and only a small number of researchers have used MDFs for pavement and transportation research. In traffic modelling, researchers have used MDF and MDA for the analysis of traffic data. Kim et al. (2014) investigated the use of MDF to analyze bus information systems and traffic card data to examine the passengers' usage patterns. Researchers suggested that this methodology can be used to design or re-organize bus service routes to save transit time. Dock et al. (2004) discussed the limitations of current roadway standards and suggested a multi-dimensional framework for the context-based design of thoroughfare.

Limited research has been conducted with MDF when looking at pavements specifically. Kuhn (2011) describes the limitations of using a discrete composite condition index and proposes that approximate dynamic programming can be used on large networks of pavements considering multi-dimensional condition data. Shrestha et al. (2017) investigated multi-dimensional highway construction cost indices. They developed an automated system to calculate multi-dimensional cost indices for enhanced work efficiency instead of spread-sheet-based systems still common among state DOTs in the U.S.

Khurshid et al. (2014) used a multi-dimensional treatment methodology to evaluate five rigid pavement rehabilitation treatments. They used American pavement performance data complemented with various other data, including climate and loading. They found that the superior effectiveness of the treatment does not necessarily translate to excellent cost-effectiveness.

The sparse existing research is supportive of the use of MDFs in the analysis of data in the transportation field. This indicates that there could be merit in further exploration.

2.2 Review of pavement data classifiers

After the selection of the MDF data structure for PaveMD, a 'classification method' (the degree of pavement performance within a wider sample) needed to be established. Several classification methods for pavement data are common in research (Figure 2).

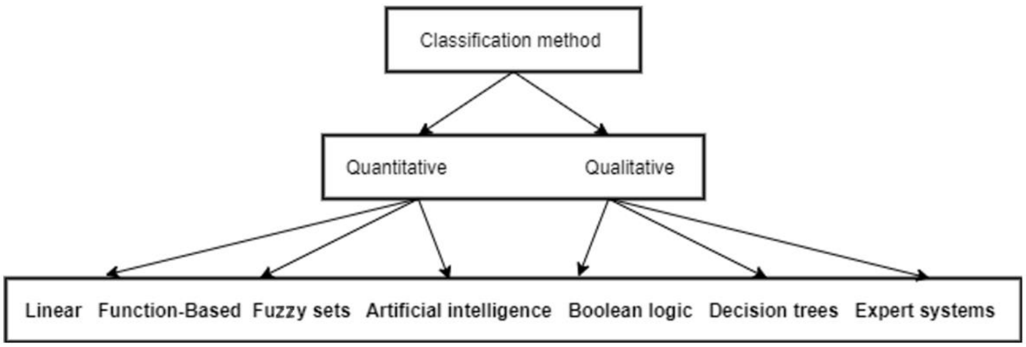

Figure 2: Classification methods reviewed are broken into quantitative and qualitative techniques.

To use existing pavement data, quantitative methods are the focus here. The advantages and disadvantages of the four candidate quantitative methods are listed in Table 1.

Table 1: The advantages and disadvantages of four different classification techniques reviewed.

	Advantages	*Disadvantages*
Linear	• Easy to implement. • Simple to understand and explain to practitioners.	• Typically not data-driven • The underlying relationship may not be linear
Function-Based	• Uses existing data to quantify performance • Typically based on correlation and regression analysis • Take more complex relationships into account.	• Necessary deterioration functions have not yet been developed for all pavement performance measures. • Models may require input variables that are not available.
Fuzzy sets	• Allows for in-depth analysis • Can be used for detailed and holistic analyses • Can describe knowledge in a human-like manner • Can be data-driven and/or use expert opinions • Uses universal classifiers	• Difficult to explain to practitioners • Variable weightings have no statistical meaning • Fuzzy rationale should not be mistaken for likelihood hypothesis • Fuzzy rationale is not exact, and outcomes may not be generally acknowledged • Fuzzy logic does not utilize machine learning
Artificial neural nets	• Ability for pattern recognition • Ability to handle large amounts of data. • Universal approximator applicable to a wide variety of pavement problems • Ability to implicitly detect complex non-linear relationships • Practitioners require less statistical training	• Black-box approach, underlying relationships are poorly understood; correlation is not equal to causation. • Consistency in output can be an issue • Software development is slow • Uses iterative approach to train neural functions • A.I. models are resource-intensive • It can be difficult to interpret results • Generalized models are difficult to implement

Fuzzy set theory was chosen because it can combine data and expert opinion to make decisions in a human-like manner. Additionally, fuzzy set theory is a common way to classify pavement data due to its many advantages to pavement engineering (Gunaratne et al. 1984; Gunaratne et al. 1985; Kucukvar et al. 2014; Pan 2008; Wang et al. 2011). The critical component of fuzzy logic is the formation of a fuzzy membership function; this is typically based on the variations in expert opinions (Tigdemir et al. 2002; Sun & Gu 2010). This research uses a modified pavement data-driven approach to establish the fuzzy membership functions.

2.3 Performance measure consolidation

Once the performance measures of each section have been classified, it is common for these to be combined with a composite index. This step is context-specific and requires a deep understanding of the qualitative relationship between different pavement performance measures and pavement performance at the network level with specific contextual factors. There are two fundamental methods to derive a composite index, these can be defined as (Fawcett et al., 2001):

1) A numeric value assigned according to qualitative rating criteria and/or road user's perception of the road or surface condition; and,
2) A statistically derived index based on quantifiable distress parameters and relative weightings.

Both forms have benefits and downsides as outlined in Table 2.

Table 2: Differences between two fundamental forms of composite indices adopted from Fawcett et al., 2001.

Qualitative composite index	
Advantages	Disadvantages
It is simple to derive since all parameter can be rated on the same scale and the outcome of the survey will determine the weighting factors (MCA).	Highly dependent on the knowledge and expertise of participants. Subjective judgement does not always reflect good engineering judgement and economic principles that can be counter-intuitive. This method is subject to the frame of reference of the survey participants
Statistically derived composite index	
Advantages	Disadvantages
The index can be derived accurately using recognized statistical approaches and analyses. Indices are founded on measurable condition parameters. It is possible to review and scrutinize the underlying reasons.	It is difficult to establish relative weighting factors. It is limited to the statistical variables in a specific context or study. This might require local calibration with specific variables that may not exist if to be applied in a different context.

Fawcett et al. suggest deriving a robust composite index largely depends on the performance measures included in the index; the method used to determine the relative weighting of performance measures; and the stability of the performance measures. For example, if the repeatability in the measurement is more subjective (rutting vs cracking) it would be more difficult to establish a robust composite index (Fawcett et al., 2001).

Depending on the country, state and province, different methods exist for developing a composite index (Henning et al., 2013, Golroo & Tighe, 2009) based on objectives and context. Here a qualitative rating criterion will be used for simplicity. A common qualitative approach to establish a simplified composite index is using a similar approach to Multi-Criteria Analysis (MCA) where performance measures are combined into a linearly formed index (Haas 1994; Shahin & Kohn 1979) as shown in Equation 1.

$$\text{Composite } Index = \sum W_i \, x_i \qquad \text{Equation 1}$$

In Equation 1, W_i represents the expert weighting, and x_i is the classified performance measure. The method establishes a unified basis to compare pavement performance measures and has been used in pavement condition assessment. Sun & Gu (2010) used the Analytical Hierarchy Process (AHP) and fuzzy logic theory to develop an approach for pavement condition assessment. They demonstrated the new methodology by ranking eight road sections using fuzzy membership functions developed by expert opinion.

Additional authors have used AHP (Moazami et al. 2011; Velasquez & Hester 2013), which is based on mathematical decision theory (Ramadhan et al. 1999; Wind & Saaty 1980). A common issue with AHP is that as the number of variables increases, the number of pair-wise comparisons increases drastically. AHP also does not facilitate discussion among experts which could yield different results (Wind & Saaty 1980).

The Delphi method presents an alternative method (Dalkey & Helmer 1963; Linstone & Turoff 1975; Ma et al. 2011; Velasquez & Hester 2013). This method is a communication technique where a panel of experts answers questions in two or more rounds (Rowe & Wright 2001). After each round, anonymous feedback is given concerning their choices and reasoning; the panel is then asked to re-evaluate their choices (Dalkey & Helmer 1963; Linstone & Turoff 1975; Ma et al. 2011).

For this research, nine pavement experts from the New Zealand National Pavements Technical Group were consulted in identifying the relative importance using three rounds of the Delphi method. This group was established in 2008 to identify and facilitate best practices for road pavement design, materials and construction in New Zealand and provide direction and advice to NZTA on research and development. This composite index developed here is further discussed in Section 5, specifically Equation 7.

3 The Development of PaveMD

PaveMD has been developed with three primary programming languages (matlab, python and SQL) and follows the Extract, Transform, Load (ETL) processes as shown in Figure 3. The data access and export components retrieve data from multiple source systems. The data transform component validates and converts data to information. The data load component checks whether the information is within expected ranges, then pushes the information into the MDF. Once the MDF has been populated, it can be evaluated with input received from the user interface.

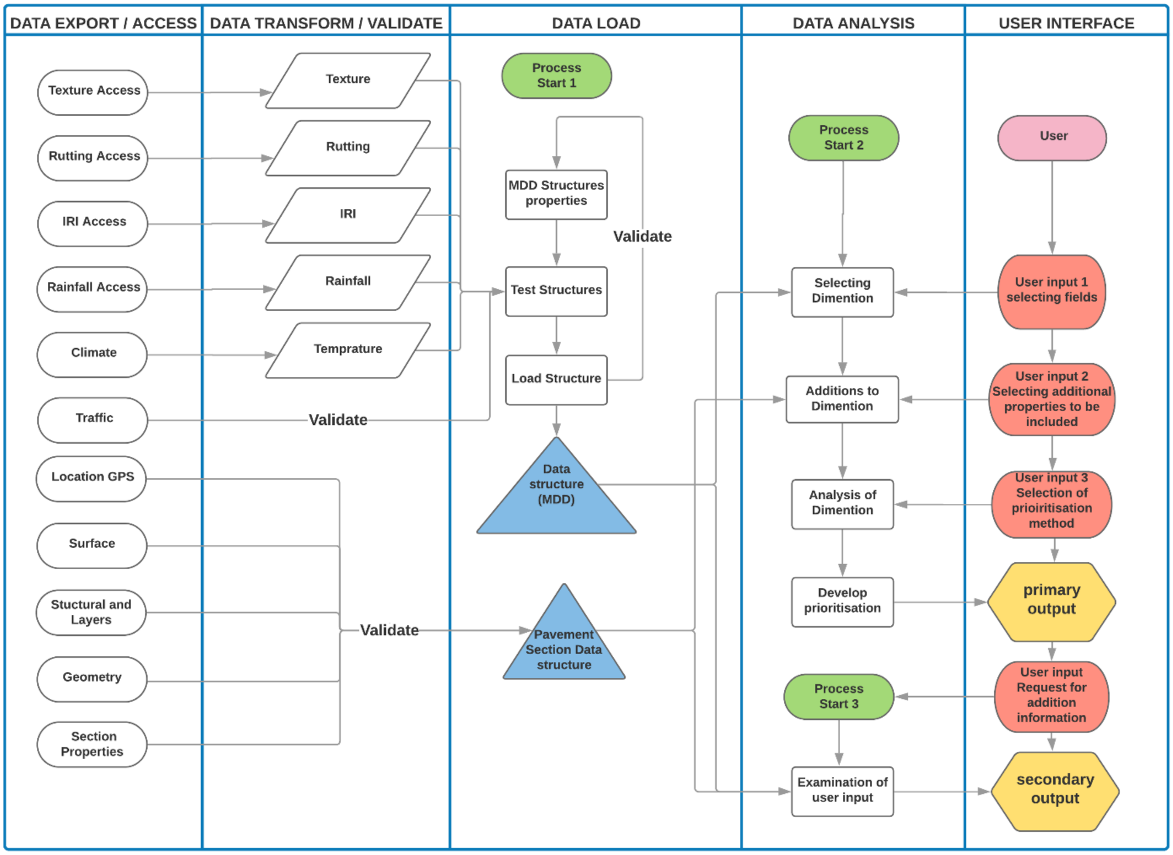

Figure 3: Extract Transform Load (ETL) procedure for PaveMD.

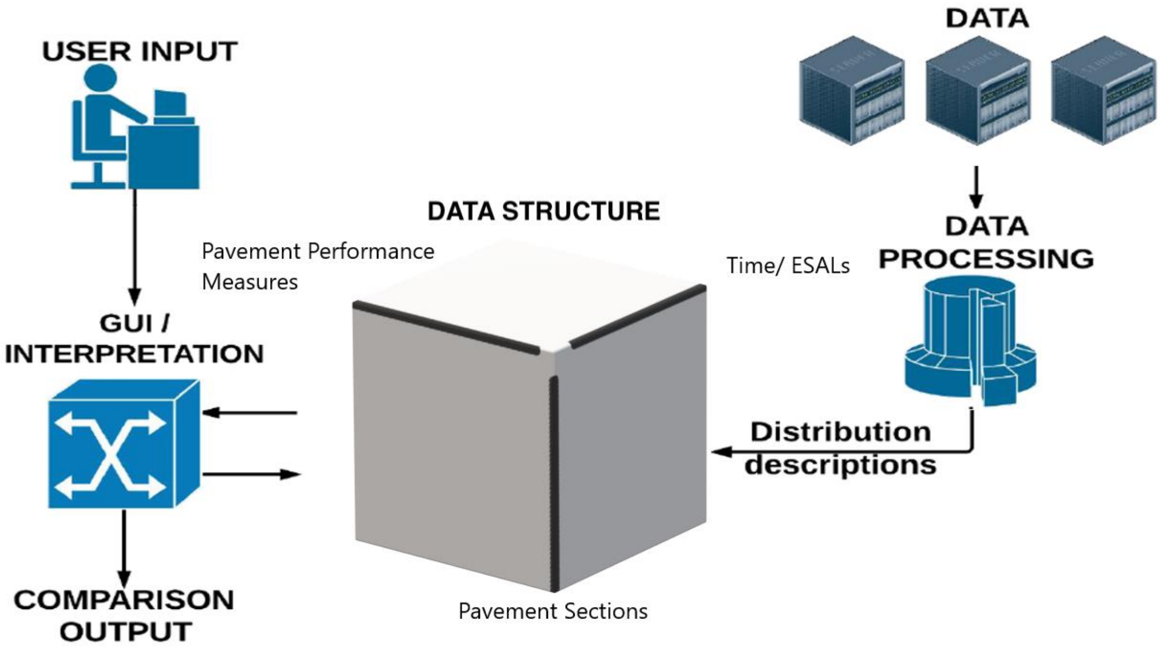

Figure 4: The Information structure of PaveMD.

The New Zealand Long Term Pavement Performance (LTPP) database was chosen to be the primary data source due to the rigour associated with its collection (Brown, 2010). The details of this database are further discussed in Section 4. Secondary data sources are from the National Institute of Water and Atmospheric Research (NIWA) and Road Assessment and Maintenance Management (RAMM) databases to add climate and maintenance information to PaveMD.

The data structure (MDF) stores distribution descriptors (log Mean and log Standard deviation, Max, Min, Mode, quality of fit parameters) instead of the raw pavement performance data. This allows for in-depth analysis without the need to access the original (very large) databases for every quarry. This method significantly increases the speed of data access and the speed of computation which allowed PaveMD to run on a single P.C. (i7-9700K, 16GB RAM). However, this does require a one-time upfront computation period to update the MDF, which depending on the data source may be time consuming.

PaveMD first gains access to different databases (authentication) and formulates performance measure distributions for each pavement section. The distribution descriptors include the mean, standard deviation, minimum, maximum, skew, and the quality of fit for each performance measure, per pavement section as mentioned previously. Fundamental distribution descriptors are chosen to enable easy recognition of the processed data. These distribution descriptors are then pushed to the centra MDF structure. While speed and minimal computational power is a significant advantage for this method, it does raise some concerns with regards to the smoothing effect when fitting distributions to performance data. This may miss representing the pavements ‘local state’ or hide severe localized issues. For a network-level analysis this is less of a concern, but on a local level using distribution descriptors may be a significant oversimplification. For this case, other methods may need to be considered to store an aggregation of the original sample from the database.

The central MDF data structure is called Stochastic Based Multi-Dimensional Matrix (SBMDM) and is the physical data structure for PaveMD. The data structure has three primary data dimensions; pavement sections, performance measures and time (ESALs), as shown in Figure 4.

The user can input various performance queries. The interpretation module translates the queries and interrogates them against SBMDM. The results are then returned to the user. The interrogation of SBMDM follows two steps. The first step is the classification of pavement performance data using Fuzzy membership functions. These fuzzy membership functions are extracted from the SBMDM.

Table 3: User assigned percentile values to the qualitative descriptors.

Percentile Value(P)	*1%(0.01)*	*25%(0.25)*	*50%(0.5)*	*75%(0.75)*	*99%(0.99)*
A qualitative descriptor for performance	Very Good	Good	Moderate	Poor	Very Poor

Each PaveMD fuzzy membership function has five membership sets, as shown in Table 3. Here the degree of performance (for example, rutting) is broken down into five qualitative measures ranging from Very Good to Very Poor. Each qualitative measure is associated with a percentile value (P). Here the values were chosen such that there is even spacing (~25%) covering the search space, however, it is recognized that this is subjective and other users or agencies may choose differently. Here we will present an example to construct the 'Moderate' membership set for rutting, one of five sets (see Table 3) to build the entire rutting membership function. This requires the following to occur.

The rutting distribution descriptors are pulled from the SBMDM for each pavement section. These descriptors are then processed per section using Equation 2, where the 50-percentile rut value is calculated for each section (see Table 3). Doing this for all pavement sections gives an array (a list) of 50-percentile values. This array is then fitted (see Figure 5) and normalized between 0 – 1 to form the 'moderate' component for the membership function (see Figure 6).

$$[VeryGood_{array\ 1-n}] = f(P, [log\ \mu_{1-n}], [log\ \sigma_{1-n}]) \quad \text{Equation 2}$$

Where,

f = Percentile Function; returns percentiles of the elements in a data vector or array for the percentage P (MathWorks Inc. 2019).

P = the corresponding percentile value (See Table 3).

n = the considered number of sections.

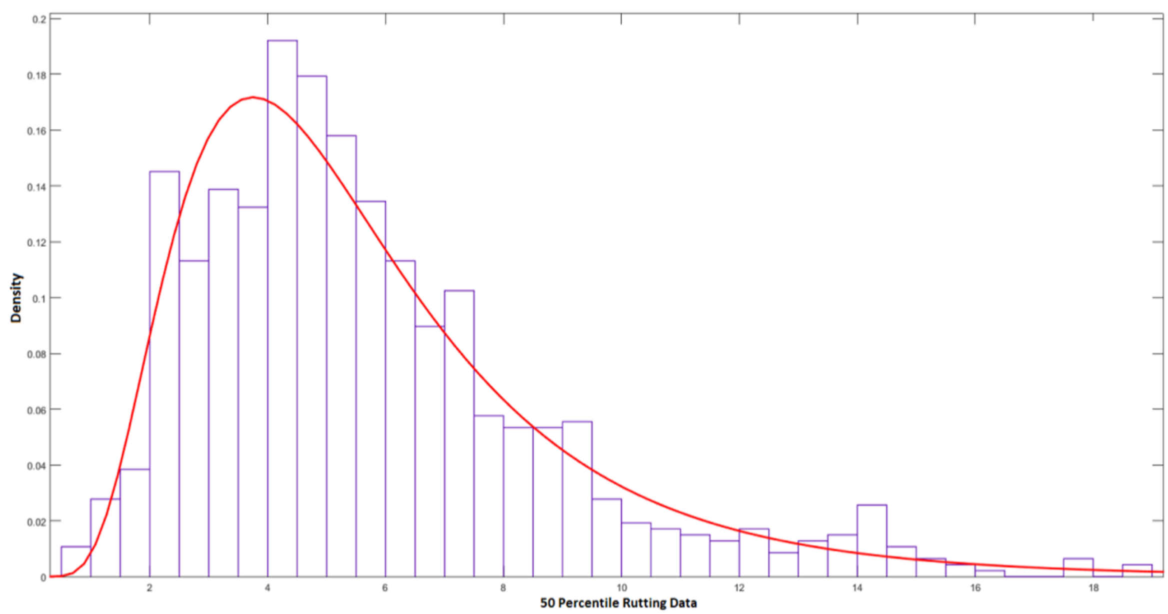

Figure 5: Fitted lognormal probability density function for 50 percentile rutting values for all sterile NZ LTPP sections (μ=1.61, σ = 0.53, mean = 5.8)

This process is repeated until each set required in Table 3 (Very Good, Good, Moderate, Poor, and Very Poor) is completed. With all five sets completed and combined; this forms the membership function for a single performance measure, rutting (see Figure 6).

The same process is then performed to construct membership functions for the other performance measures (IRI and Texture), see Figures 7 and 8. It is important to note that some performance measures are advantageous (show a higher degree of performance) in ascending order (for example texture), where others, are advantageous in descending order (for example rutting). This changes the orientation of the membership functions.

Once the membership functions have been formed, the Rational Set (R) and Normalized Rational Set (NR) can be formed (Equation 3 and 4). In the Rational Set a single performance measure is broken up into the five discrete indices, the qualitative descriptors for performance. These indices are constructed from the membership functions as developed above. This is different from a traditional approach where each pavement section would be allocated a single index. For a further detailed explanation of fuzzy logic, please see research done by Sun et al. (Sun & Gu, 2010).

Note that once the distributions are normalized to form part of the fuzzy membership functions, they lose statistical meaning. A value of 0.4 for a membership function does not imply a probability of 0.4. The area under the curve does not sum to 1 as it should for a probability distribution. Instead, the normalized distribution conveys the degree of membership to the distribution.

$$R = [VGood_{DoM}, Good_{DoM}, Moderate_{DoM}, Poor_{DoM}, VPoor_{DoM}] \quad \text{Equation 3}$$

$$NR = [\frac{VGood_{DoM}}{Sum(R)}, \frac{Good_{DoM}}{Sum(R)}, \frac{Moderate_{DoM}}{Sum(R)}, \frac{Poor_{DoM}}{Sum(R)}, \frac{VPoor_{DoM}}{Sum(R)}] \quad \text{Equation 4}$$

Where *R* is the array of values that show the degree of membership (DoM) of each of the qualitative descriptors, and *NR* is the normalized rational set.

The next step is the consolidation of the performance measures. This is done using a normalizing weighting vector that indicates the importance of different performance measures to pavement success. Qualitative composite index W, is context-specific and contains the three values of the respective weightings of Rutting, IRI and Texture. The Delphi approach was used here to develop W, as outlined in Section 2.3.

To consolidating fuzzy relational sets, the weighting vector is combined with the fuzzy normalized Relational Sets, as shown in Equation 5.

$$EvaluationSet = W \otimes NR \qquad \text{Equation 5}$$

If the Evaluation Set (Equation 5) is analyzed to find the largest index value, a winner takes all approach (WTA) can be used to classify all sections into one of five groups: *VeryGood – VeryPoor* (corresponding WTA index, 1-5). This is a simplistic method of identifying pavement sections that are performing well.

A more rigorous approach; multiplying the Evaluation Set with a quantifying vector, for example, the normalized vector [5; 4; 3; 2; 1] will produce a finite rank index called the defuzzified weighted cumulative index (DWCI) as suggested by (Sun & Gu, 2010), this is shown in Equation 6.

$$DWCI = \ Evaluation\ Set * \begin{bmatrix} 0.333 \\ 0.267 \\ 0.200 \\ 0.133 \\ 0.067 \end{bmatrix} \qquad \text{Equation 6}$$

When combining this method above with the SBMDM, it becomes a powerful tool that allows decision-makers to analyze pavement data from multiple views (dimensions). This will be demonstrated in the case study below.

4 Case study –Classifying NZ LTPP sections

The data from the NZ LTPP program is the focus of the case study. The LTPP includes roughly 130+ pavement calibration sections from both local authority and state highway roads. These calibration sections are typically 300m in length and measurements (rutting, roughness and texture) are reported at 10m intervals. Consultants collect data to a rigorous methodology (for more information see Brown, 2001) in both directions, in both wheel paths, in the same location yearly since the program's inception in 2001. In addition, the transverse profile, including rutting, is collected with a specially designed transverse profile beam (TPB). Roughness information is collected by experienced surveyors with the ARRB Walking Profiler. Texture measurements are collected with Transit Stationary Laser profiler, a New Zealand reference device. This device collects data in the 0.5mm to 500mm wavelength; the data is post-processed to Mean Profile Depth (MPD) following ISO13473-1. To ensure repeatability, measurements are taken multiple times and checked for consistency (Brown, 2010). As-built constructed information for many sites did not exist due to the age of the roadways, therefore detailed test pit information has been collected for the calibration sections.

The original purpose of the LTPP program was to calibrate the New Zealand pavement deterioration models (Henning, 2006; Henning, 2008; Henning et al., 2009). The LTPP program in NZ consists of ‘sterile’ and ‘non-sterile pavement’ sections for modelling purposes. Sterile sections have only received maintenance if this was necessary for safety reasons whereas non-sterile sites are under normal maintenance schedule. For this case study, these 75 sterile LTPP sections have been analysed. Showcasing all 75 sections in this paper would be impractical and add no theoretical knowledge. Instead, ten sections with a diverse range of associated properties are showcased here (see Table 4); similar to Sun & Gu, 2010 who only showed eight sections. The three key performance measures considered from the NZ LTPP are rutting (in mm), roughness (IRI) and texture (MPD) with respect to time (ESALs).

Table 4: Ten LTPP sections with associated properties

Pavement section	*Surface*	*Base thickness*	*Base type*	*Sub-base thickness*	*Sub-base type*	*AADT*	*% Heavy vehicles*
'CS_22'	Chip-seal	90	AP40	190	AP40	1012	18
'CS_24'	Chip-seal	90	AP40	80	AP65	1448	18
'CS_29'	Chip-seal	95	AP40	480	AP40	1723	12
'CS_60'	Chip-seal	-	-	-	-	2239	10
'CS_20'	Chip-seal	270	AP65	150	SILT	2403	15
'CS_26'	Chip-seal	100	RR	-	-	2825	17
'CS_14'	Chip-seal	140	AP40	260	AP65	4214	10
'CS_33'	Chip-seal	100	M4	-	-	8096	5
'CS_11'	Chip-seal	130	AP40	130	SAND	8644	4
'CS_7a'	OGPA	125	AC	380	AP40	82530	8

4.1 Case study results

PaveMD was used with all sterile NZ LTPP data to develop pavement performance membership functions shown in Figures 6-8. In Figure 6, the membership functions of rutting are shown. There are five membership functions to classify a single rut value varying from *Very Poor* to *Very Good*. For each rutting depth on the x-axis, the corresponding degrees of membership to the five classifications are depicted on the y-axis. Similarly, in Figures 7 and 8, the membership functions for IRI and texture are depicted.

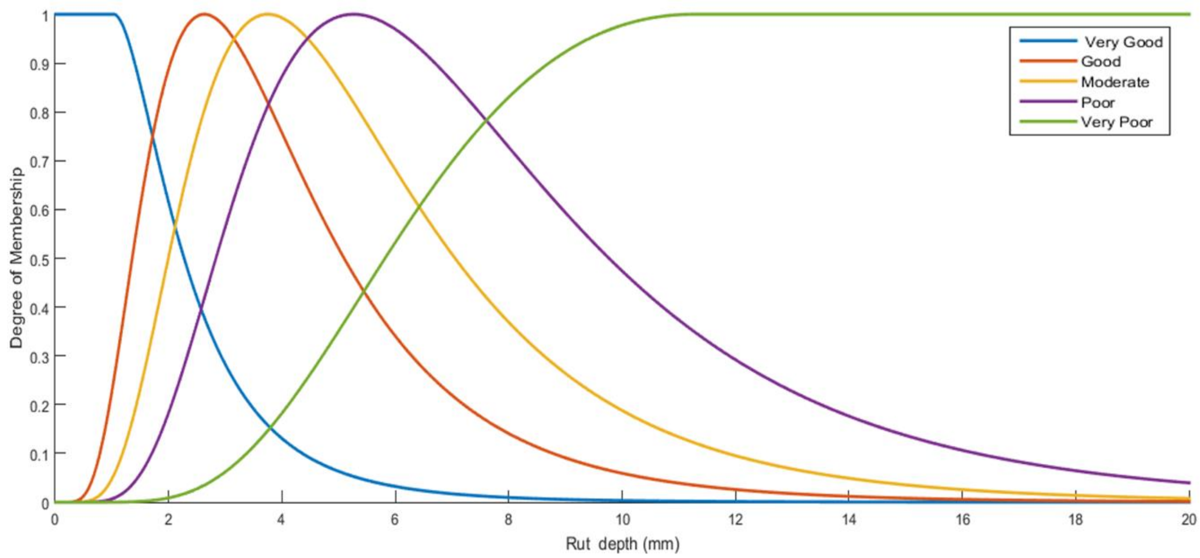

Figure 6: Rutting membership functions constructed from all sterile (no maintenance) New Zealand LTPP sections.

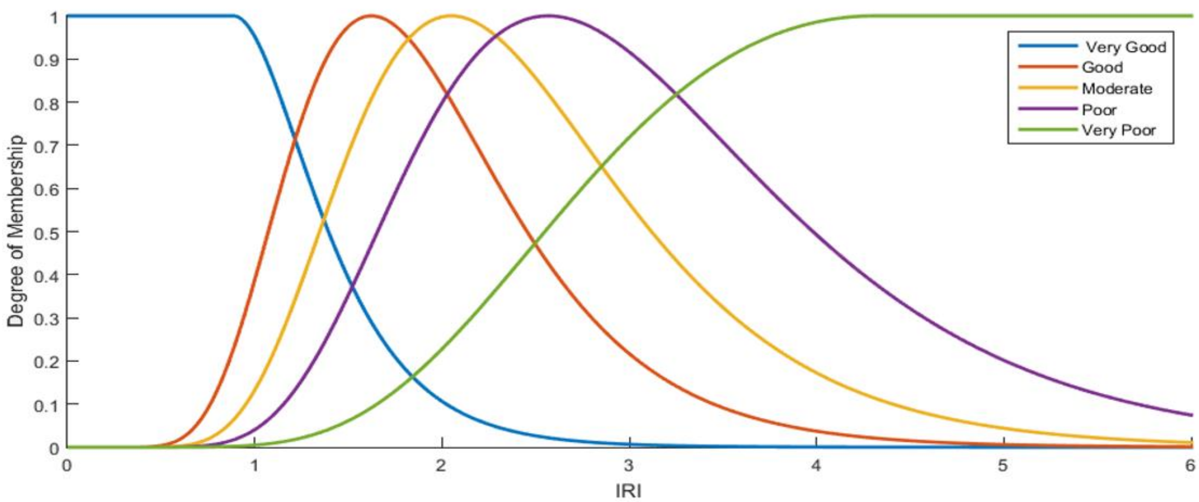

Figure 7: IRI membership functions constructed from all sterile (no maintenance) New Zealand LTPP sections.

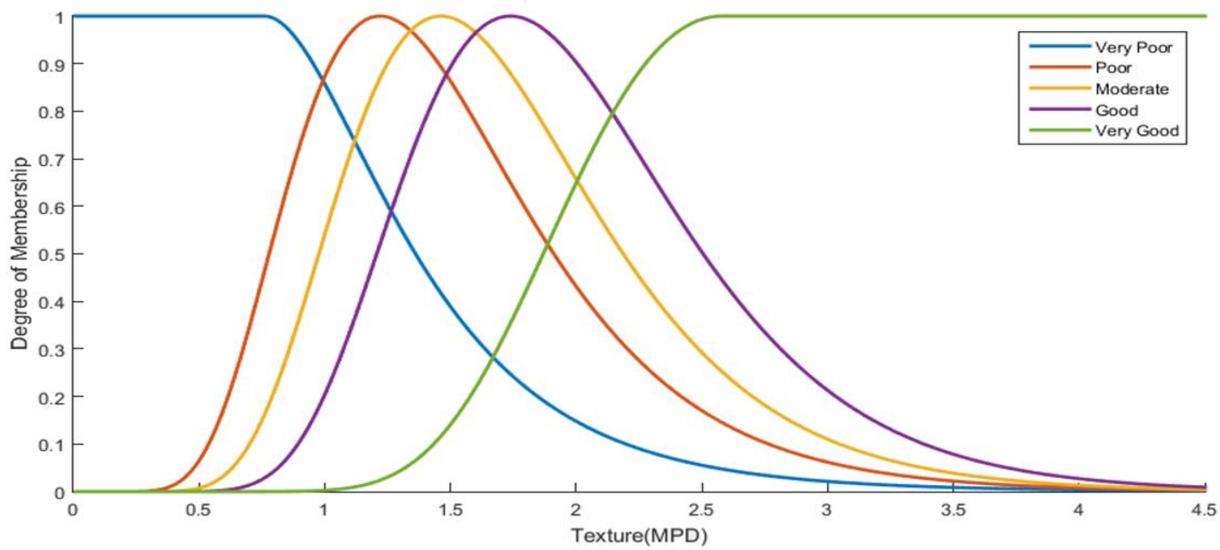

Figure 8: Texture membership functions constructed from all sterile (no maintenance) New Zealand LTPP sections.

A composite index (W) has been established to combine rutting, IRI and texture. The normalized W (Equation 7) for a network-level was established by the New Zealand National Pavements Technical Group's experts following the Delphi method (Linstone & Turoff 1975).

$$W = [\,Rutting(W_1), \quad IRI(W_2), \quad Texture(W_3)] = [0.45\,, 0.35, 0.2] \qquad \text{Equation 7}$$

From Equation 8, it follows that rutting is the most influential performance measure when determining the pavement performance, followed by IRI and then texture. With this, the relative pavement performance in the New Zealand context can be calculated.

Table 5 shows the ten showcased LTPP pavement sections ranked to DWCI. Here section CS_7a is performing the best, whereas section CS_22 is performing the worst. From this table, we can also see that the simplified method, the WTA index corresponds well with the DWCI. Section CS_7a has a degree of membership of 0.364 for the *Very Good* descriptor, the highest degree of membership which gives it a WTA of 1. This corresponds well with CS_7a's high DWCI value of

0.223, indicating high performance. It is interesting to note that although section CS_7a did not have a texture value recorded in the database, it was still ranked first in DWCI. This is because there was very little weight put on texture. It performed exceptionally well in the other two performance indicators. Having missing data for a performance measure is an advantage with regards to the WTA score, however, would be a disadvantage to the DWCI score.

Table 5: LTPP sections ranked to the defuzzified weighted cumulative index (DWCI) as suggested by (Sun & Gu 2010).

Section	*DWCI*	*WTA*	*Very Good*	*Good*	*Moderate*	*Poor*	*Very Poor*	*Rutting*	*IRI*	*Texture*
'CS_7a'	0.223	1	(0.364	0.261	0.127	0.044	0.003)	1.985	0.960	-
'CS_26'	0.200	3	(0.065	0.287	0.312	0.261	0.076)	4.505	1.592	1.500
'CS_33'	0.191	4	(0.136	0.172	0.253	0.296	0.143)	6.064	2.279	2.794
'CS_20'	0.179	4	(0.029	0.207	0.307	0.327	0.129)	4.954	2.446	1.628
'CS_24'	0.167	4	(0.043	0.182	0.248	0.297	0.230)	8.057	2.138	1.864
'CS_11'	0.156	5	(0.077	0.133	0.187	0.256	0.347)	10.810	2.454	2.237
'CS_14'	0.154	5	(0.081	0.108	0.180	0.307	0.323)	7.801	3.399	2.298
'CS_29'	0.151	4	(0.011	0.129	0.244	0.345	0.271)	5.201	3.637	1.259
'CS_60'	0.141	5	(0.012	0.108	0.206	0.332	0.342)	8.584	3.114	1.519
'CS_22'	0.124	5	(0.005	0.091	0.169	0.228	0.506)	16.022	2.329	1.027

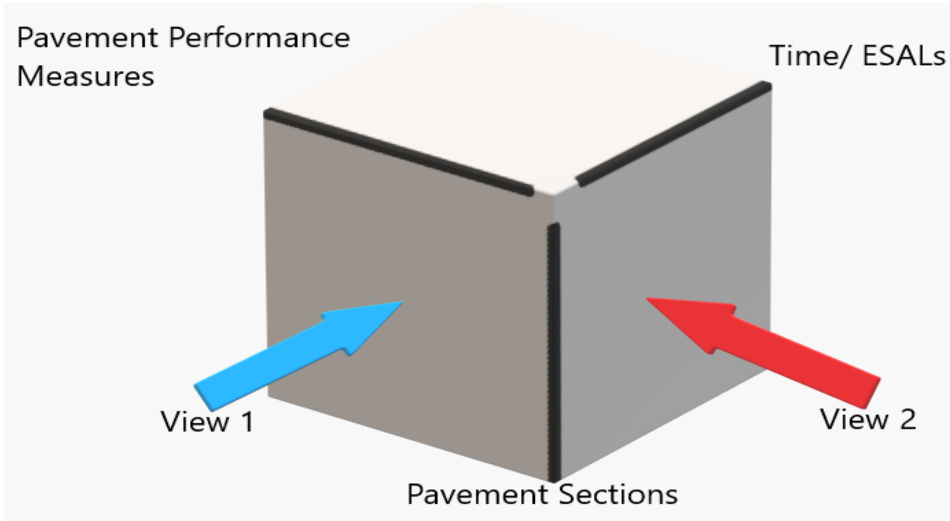

Figure 9: Abstracted diagram of the SBMDM.

A significant advantage of the multi-dimensional approach is the ability to select data from different perspectives (dimensions). Thus far, 'View 1' has been examined as denoted in Figure 9 with 'Pavement Performance measures' and 'Pavement sections' as the edge parameters. Next, 'View 2' in Figure 9 will be queried. View 2 has the edge parameters' Time/ESAL's and 'Pavement sections'. The ranking of the pavement sections on a single performance measure against time (ESALs) is shown in Table 6.

Table 6: LTPP sections that have been identified by DWCI, considering rutting only over time (ESALs)

Pavement section	*DWCI*	*WTA*	*Very Good*	*Good*	*Moderate*	*Poor*	*Very Poor*
CS_7a'	0.102	2	0.121	0.124	0.101	0.061	0.007
'CS_26'	0.073	4	0.008	0.069	0.124	0.162	0.085
'CS_29'	0.071	4	0.006	0.062	0.120	0.167	0.093
'CS_33'	0.071	4	0.006	0.061	0.118	0.165	0.098
'CS_20'	0.063	4	0.004	0.045	0.097	0.158	0.144
'CS_24'	0.062	5	0.005	0.044	0.088	0.145	0.166
'CS_14'	0.061	4	0.003	0.040	0.091	0.157	0.157
'CS_11'	0.049	5	0.002	0.020	0.052	0.112	0.262
'CS_22'	0.038	5	0.000	0.005	0.019	0.063	0.361
'CS_60'	0.035	5	0.001	0.018	0.047	0.094	0.116

The order of sections in Table 6 is not significantly different from that in Table 5. This shows that rutting governed the selection as it received the largest weighting (W_1) in the results from Table 5.

This view allows for a detailed comparison of the performance of all sections for a single performance measure. It is also possible to give different weightings to various years of service; for example, the 10th year of service could be valued more than the first or the second year by the user. Thus classifying sections across the entire recorded pavement life with respect to one performance measure. In addition, we rank the sections against time, according to DWCI and WTA, using all performance measures and W. This presents a holistic view of all data available in SBMDM (all dimensions; Pavement sections, performance measures, time/ESALs). These results are shown in Table 7. Here section CS_7a is the highest performing while CS_60 is the worst.

Table 7: The ranking of sections over time, according to DWCI and WTA, using all performance measures.

	Overall DWCI	*Rutting DWCI*	*Rutting WTA*	*IRI DWCI*	*IRI WTA*	*Texture DWCI*	*Texture WTA*
CS_7a'	0.117	0.102	2	0.202	1	0.000	NAN
'CS_33'	0.116	0.071	4	0.130	3	0.190	1
'CS_26'	0.109	0.073	4	0.153	2	0.114	4
'CS_24'	0.105	0.062	5	0.134	3	0.151	2
'CS_20'	0.097	0.063	4	0.124	4	0.128	3
'CS_14'	0.089	0.061	4	0.092	5	0.149	2
'CS_11'	0.088	0.049	5	0.115	4	0.129	3
'CS_22'	0.085	0.038	5	0.127	4	0.115	4
'CS_29'	0.080	0.071	4	0.083	5	0.095	4
'CS_60'	0.055	0.035	5	0.062	4	0.086	3

This process has identified pavements that are performing well, considering the three performance measures. This identification could then be followed up with a more detailed investigation to find the underlying reasoning. This priority can also be used to identify pavement sections that require maintenance at a network level.

5 Discussion, limitations and recommendations

5.1 Application of PaveMD

This study proposed a tool to assess pavement conditions, prioritize maintenance, and identify good performing pavement based on multi-attribute performance measures. It provides a systematic way of characterizing previous subjective ratings using performance data. By creating an evaluation set with five categories Very good, Good, Fair, Poor, and Very poor, the agency or user can assess their evaluation of performance. For example, here 50 percentile has been assigned as "moderate", PaveMD will assess the SBMDM and return the membership function based on this 50 percentile assignment.

The procedure presented in this paper can be generally applicable to the condition assessment of other infrastructure where multi-attribute are presented with an adequate amount of data. When applied, specific membership functions and composite indices need to be re-established as appropriate following the specific type of infrastructure and context.

5.2 The use of PaveMD beyond this paper

The development of PaveMD has spanned years and a selection of research studies have successfully used the capability of PaveMD during its development. PaveMD was used in the Canterbury region of New Zealand to identify and investigate high performing chip-seal pavement sections, which led to a relationship between pavements performance and road camber being identified (van der Walt et al. 2018). PaveMD was also used at the network level with the entire New Zealand LTPP dataset (van der Walt et al. 2017). This showed that network data discrepancies were consistent with the condition assessment models developed by Henning et al. (Henning et al. 2009). This research also suggested that further development could lead to extended maintenance periods by stiffening the outside wheel path.

5.3 Constraints

Researchers and users must recognize that both the classification step and composite index used with PaveMD are context-specific. In the LTPP case study, a holistic view was taken that included all sterile LTPP sections. Hennings (2008) showed the LTPP sections are representative of the New Zealand network. This meant that the position and variability included in the membership functions (Figure 6-8) is a good representation for the New Zealand pavement network at the time of writing; predominantly for a chip-seal pavement network. For the investigation of a specific area or region, both the classification step and composite index used must be re-assessed using a subset of the section data.

A key limitation to this approach is the quantity and quality of the available data. Data-driven membership functions can only be constructed if a statistical distribution can be fitted accurately. As the specificity is increased, the amount of data will reduce to a point where distributions can no longer be reliably established. At this point, the membership functions lose significance and therefore, rankings are no longer dependable. This could be of particular concern for pavement databases that have missing and or incorrect data, for example, local roads as compared to state highways. However, as big data collection becomes commonplace with technologies such as the Internet of Things, and high-speed data collection, the approach presented here will become more robust as membership functions become more accurate.

A constraint of this approach is the development of the composite index (W) using an expert method like the Delphi method. While this approach is firmly based in literature, statistical methods to derive W should be investigated.

5.4 Further research

The development of PaveMD is ongoing to allow for additional expandability and capability.

- Include statistically derived pavement composite indices, both for surface and structural parameters for example Structural Indices(SI) as suggested by Stevens et al, 2009.
- Increase the number of performance measures, including cracking and Falling Weight Deflectometer measures.

A promising research area in data analytics is columnar data structures or Column-Oriented Database Management Systems, for example, ClickHouse (ClickHouse, 2021) and Apache Casandra (Cassandra, 2021) which could bring additional advantages to pavement data analytics. Advantages include, for example, lower overheads when importing data to the database, improved compression of data, improved parallel processing on multiple CPU cores and additional reading efficiency. Aggregation across a data field (for example, finding the average rut depth for a pavement network) can become much more efficient, taking seconds instead of days to compute across terabytes of data. These advantages must be balanced with disadvantages and therefore, further research is needed.

6 Conclusions and Recommendations

Advancing technologies enable the creation of tools that utilize pavement data more efficiently. The fundamental approach 'to repeat success' proposed by Gransberg et al. (1998) has been used in conjunction with software to develop a new tool. This tool, called PaveMD, uses a multi-dimensional, fuzzy logic approach to identify pavements that are performing well at the network level. Instead of using an expert system, membership functions have instead been established using existing pavement performance data. This research demonstrates the tool using a case study from the New Zealand Long Term Pavement Performance program where PaveMD successfully classified pavement sections at the network level.

This paper has the following recommendations for further research.

- Further research should expand the number of performance measures from different databases, including other climate and geo-hazard databases. As a priority it is recommended to extend PaveMD to Falling Weight Deflectometer (FWD), cracking and drainage information.
- Individual pavement composite indices, both for surface and structural parameters for example Structural Indices should be investigated.
- Investigate other data frameworks such as Column-Oriented Database Management Systems to analyze pavement performance data.

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