

Kadar, Martin Baran and Sen

ADDRESSING UNCERTAINTIES OF PERFORMANCE MODELLING WITH STOCHASTIC INFORMATION PACKAGES – INCORPORATING UNCERTAINTY IN PERFORMANCE AND BUDGET FORECASTS.

DR PETER KADAR, PRINCIPAL RESEARCH ENGINEER, ARRB GROUP (CORRESPONDING AUTHOR), 2 – 14 Mountain Street, Ultimo, New South Wales, Australia

DR TIM MARTIN, CHIEF SCIENTIST, ARRB GROUP 500 Burwood Highway, Vermont South, Victoria, Australia

MICHELLE BARAN, MANAGER (STRATEGIC ASSET MANAGEMENT) QTMR, Terrica Place, 140 Creek Street Brisbane Queensland Australia

RANITA SEN ASSET MANAGEMENT ENGINEER, ARRB GROUP, 2 – 14 Mountain Street, Ultimo, New South Wales, Australia

Date of submission: 27 August 2014

Word count: $4199 + 7 \times 250 = 5949$

ABSTRACT

A large volume of data is collected world-wide to feed pavement management systems (PMS). The data is typically condensed to characterise pavement sections or smaller sub-networks by using statistical measures – mostly averages. In this process valuable information is lost, thus increasing the likelihood of providing inaccurate or in some cases misleading answers. The pitfalls of using averages can be avoided by utilising the full data set and treating each data set as an entity or stochastic information packet (SIP). Modelling with SIPs means that the input as well the output of the modelling is a distribution as opposed to the singular outcome of deterministic models. The resulting distribution allows determination of the probability of the outcome besides its predicted value. Budget and condition forecasts therefore may include not only the future condition and budget requirements, but their reliability and consequently the level of associated risks. Managing agencies and contractors may choose the budget scenario best reflecting their level of risk acceptance or tolerance. Modelling with SIPs builds on deterministic models by expanding their outcomes into full distributions. Working with arrays (SIPs) requires using a novel approach that is described and illustrated in the paper.

INTRODUCTION

Pavement management systems (PMS) require data that accurately reflect the properties and other operating circumstances of the network. It is a well-known, but largely ignored, fact that much of the information is uncertain or poorly represented (note that the term uncertain is used to describe both), either due to the intrinsically variable nature of the data (e.g. the environment) or due to the data aggregation process. Ignoring the uncertain nature of the input transfers the level of uncertainty to the output without acknowledging, let alone, quantifying it.

Deterministic models are widely employed in pavement management systems to forecast future performance. These models typically use averaged (assumedly representative) data as input. The models are typically based on a statistical relationship determined by curve fitting to a scatter of observations. At best this delivers a result with equal chance that the true value is either below or above predicted the predicted one. Depending on the level of data aggregation, including the chosen analysis lengths, the forecast may be grossly misleading and thus inherently inaccurate. The underlying concepts and ideas of the need for a risk-based, or as often termed, probabilistic approach are discussed in detail and illustrated elsewhere (1).

The adopted approach addresses the level of uncertainty by applying a probabilistic approach to the modelling of pavement performance. The approach utilises the full set of historical data and forecasts the probability distribution functions (PDFs) of key variables. This allows the degree of uncertainty of the forecast to be ascertained, so that the budget for a given level of service (LOS) can be determined with a known degree of reliability. Thus the road agency can determine the level of uncertainty it desires or can afford and incorporate it in their budget forecast. Alternatively, the effect of a fixed budget on network performance can be determined with a quantified level of certainty.

LOST INFORMATION DUE TO USING AVERAGES

The lost information due to condensing the data into a single figure are illustrated by the analysis of select long term pavement performance (LTPP) data collected over 12 years in Australia. The full rutting data time series is presented as a series of cumulative histograms in Figure 1. The data distribution is presented here in terms of cumulative histograms as this form lends itself best

Kadar, Martin Baran and Sen

for analysis and visualisation. The 2000-2002 histograms are relatively close to each other, indicating that the whole section deteriorates about the same rate. The 2003 data indicates a significant deterioration on a substantial part of the section. After treating the pavement in 2004, the shape of the histogram returns close to the original and further deterioration is indicated over the full section by the close to parallel shifts of the annual histograms.

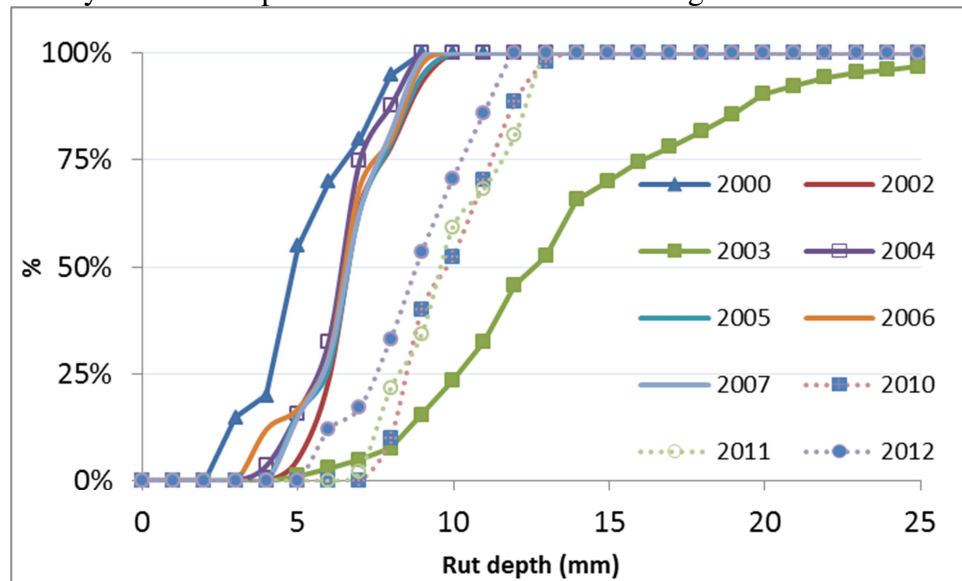


FIGURE 1 Rutting data collected at a LTPP site (Source: 3).

The analysis of the annual data presented as cumulative histograms gives rise to the following considerations:

- The general slope of the histogram indicates the uniformity of the section; a vertical or near vertical histogram indicates very small scatter of the data, i.e. a high level of uniformity. In this, rather rare, case the average may be considered as representative of the data set. A pronounced decline or ‘leaning’ of the histogram reflects a substantial scatter, a wider standard deviation, in which case the average is less than adequate representative of the data.
- Parallel shifting of the histogram over time indicates that the whole section changes at a similar rate, i.e. the scatter of the data also expressed as the standard deviation remains more or less the same, but all data points shift in the same direction. In this situation whilst the limitations of the average remain valid, models based on averages reflect the changing trend correctly, even if the numerical value of the change is limited to a percentage of the population.
- The change of the slope of the histogram indicates an increase of the range and scatter of the data. This means that the road section does not behave uniformly as some parts of it deteriorate faster than others. The proportion changing at a different rate can be quantified by the percentiles. In this case forecasts based on averages would misrepresent the overall trend as they are not true for the whole population but only for an imaginary average.

The behaviour of data distributions illustrated in Figure 1 is not unique; it can also be observed in other data sets (3). The use of the full data set opens up several opportunities.

Kadar, Martin Baran and Sen

- The uniformity of a section can be quantified by observing the slope of the histogram; it is suggested that the slope between the 20th and 80th percentiles be used for this purpose.
- The proportion of the section affected by deterioration can be quantified; this is particularly relevant for determining the areas to be treated, thus costs can be determined more accurately.
- The treatment history of the section can be deduced from the analysis of the histograms; changing shape and particularly the shift towards improved values indicates remedial treatments. The change of shape even allows estimating the length (proportion) of the section treated previously. (In Figure 1 the rehabilitation of the pavement is signalled by the histogram returning to its original state).
- The recognition of past remedial works assists in the calibration and development of models, as irrelevant data (i.e. data that refers to a removed or repaired state) that can be excluded from the model development. Without the knowledge of remedial treatments, trends can be misleading.
- Last, but not least, new models can be developed to predict the extent of specific distress, such as rutting and cracking, rather than predicting the average deterioration of distress.

The analysis of the data distribution requires some practical considerations, such as storage and efficient access to the full data set. Traditional data formats in conventional databases would be quickly overwhelmed with the quantity of data as these are geared towards storing disparate data items. A practical solution to store full data sets is possible when the data is condensed as suggested in (1) as Stochastic Information Packages or SIPs.

A data set may be stored as a single text string in a coded (XML) or un-coded (e.g. CSV) format. The CSV format is familiar to most Excel users. The converted SIPs can be stored in a single Excel cell or as a 'navchar' or 'XML' type attribute in most contemporary databases such as SQL Server. The condensed SIP may carry additional information, such as the standard used for condensation, the source of data, the minimum, maximum and average values as well as the number of data elements included. The precision of the data compression can be controlled by most standards, so adequate accuracy may be achieved when recovering the SIP.

The condensed data typically occupies about 10% of the space required by the full data and takes up only a single cell in Excel or a single database item in a suitable database. This opens up several possibilities for this data format, as it makes it eminently suitable for carrying large data sets in a very small space. Though hard disk space and storage is becoming cheaper by the day, easy portability is considered a significant advantage. More importantly, instead of storing aggregated data, the full data can be stored in readily available databases.

UNCERTAIN VARIABLES

It is generally assumed that the data used for managing assets is a true representation of the asset's properties, condition and the operating environment. In reality the input parameters are far from being definitive and thus contain a degree of uncertainty.

Uncertainty of the input data stems from one or more of the following circumstances:

- **Information Quality Level (IQL);** the quality of the collected data is critical when considering uncertainty. Detailed network level data (IQL-3 and IQL-4), e.g. data collected with high speed electronic devices, will have a lower level of inherent uncertainty than data obtained at IQL-5, e.g. by visual observation or perusing records. (2).

- **Data aggregation** is required to generate a single representative number from the detailed data for a road section. Most frequently the average of the data is used for representing the property of a section. Averaging data may misrepresent the nature of the data and in most cases dismisses valuable information on the spread and shape of the data distribution. Actual failure or reduced LOS of the infrastructure is related to the worst and not to the average condition, hence the spread of the data and its extreme values are critical. The uncertainty related to data aggregation is also a function of the road segment size; the larger the segment the less likely to be uniform. For example, average rutting means very little on a longer road segment that may include short heavily rutted sections and longer sections with minimal rut depth.
- **Environmental data** is an extreme case of data aggregation as valuable time series data is compressed into a single parameter such as the weighted annual mean pavement temperature (WAMPT). However, pavement performance is related to the environment at the time of the application of the traffic load, hence even a weighted average of temperature, rainfall etc. can distort the outcome.
- **Cost** information, unit rates, tend to vary significantly, depending on several factors ranging from the location and timing of the contracts to the type of contract. Consequently, the average treatment costs do not reflect the likely scatter of treatment costs.
- **Insufficient or estimated data** is uncertain by definition. Typically traffic forecast and annual average daily traffic (AADT) data fall into this category as these are based on sampling the traffic at various locations and times. Where no data is available, alternatives may be sought to obtain at least approximate, thus uncertain, information (8).
- **Material properties and construction quality** are either estimated or more often than not are assumed only based on local experience.
- **Calibration factors** are required for most models. Calibration is usually conducted at selected locations and the results are then projected for all similar pavements. This process assumes that the selected locations and thus the calibration, is representative. In reality the derived calibration factors display a scatter (distribution) that should be taken into account.
- **Variability of measurements** is an ever present fact that has, however, a lesser magnitude on its own compared to the other issues listed above, particularly when using advanced technologies.

Analysis (3) indicated a large variety of probability distribution functions (PDF) for typical pavement deterioration input variables; Thornthwaite Moisture Index (TMI), initial modified structural number for the pavement/subgrade (SNC_0), traffic load (MESA), annual average maintenance expenditure (me), seal life and initial roughness (IRI_0) as shown in Figure 2. Furthermore, the shape of the distributions is prone to change from locations to location.

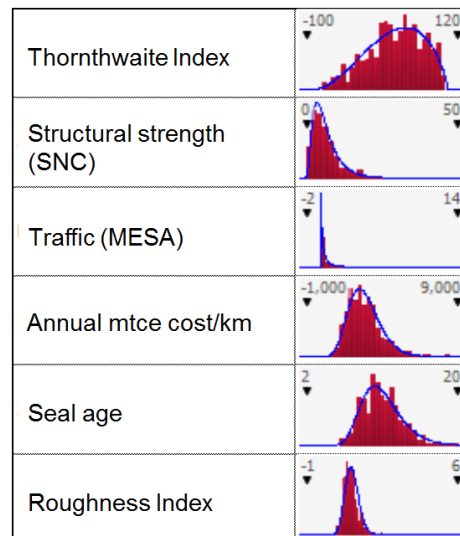


FIGURE 2: Probability distribution functions (PDF) of selected input parameters to pavement deterioration models.

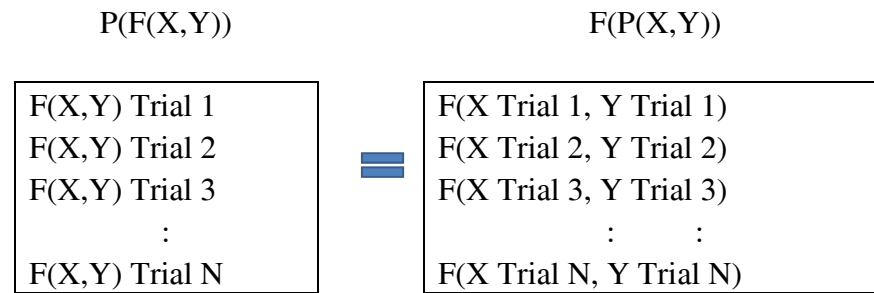
The logical solution to address uncertainties is to take the full distribution of the measured input data into account.

MODELLING WITH SIPs

The most commonly considered approaches for addressing uncertain variables are based on either Markov chain modelling or Monte Carlo simulation in combination with deterministic road deterioration (RD) models. Markov chain is typically used when no historical data or trend is available. Markov chain models tend to show rapid deterioration before reaching equilibrium or terminal condition. When pavement condition data is available and suitable deterministic models have been developed (4,5), the use of Markov chain models cannot be justified.

Monte Carlo simulation offers several advantages, such as accommodating a wide range of input data using probability distribution functions and easy incorporation into RD models. Monte Carlo models require a mathematically defined distribution i.e. fitting a distribution function to a wide range of data for each location and road segment. This is a rather time consuming task usually requiring human involvement and supervision. Monte Carlo simulation is also time-consuming, considering the quantity of simulation to be carried out in a PMS. A pavement deterioration model usually includes at least four distress modes, (rutting, cracking, roughness and strength), requiring at least four Monte Carlo simulation for every year; assuming a network of 1000 segments and a 20 year analysis period, the number of simulations would reach well over 80,000. As for each segment and year several options need to be explored, the number of simulations would be closer to 1,000,000 than 100,000. A potential solution to replace Monte Carlo simulation with a simpler option is proposed (1).

SIPs may be treated as arrays and can be used in calculations as such. In expressions when two or more SIPs are involved, all SIPs must be of the same length. When SIPs are independent, the sequence of the data in a SIP is not relevant. However, when SIPs represent interrelated data, the sequence of these must be maintained. The generic concept of SIP operations is shown in Figure 3.



Where $P(F(X, Y))$ is the SIP of $F(X, Y)$

FIGURE 3: The generic concept of SIP arithmetic (Source: (1)).

Operations with SIPs can effectively replace Monte Carlo simulation, assuming that a SIP contains a sufficiently large number of constituents. In the discussion below the term SIP denotes a scatter or distribution of the data to underline the fact that the full data is considered and not just a statistical characterisation of it. A practical implementation of SIP arithmetic developed by Thibault (6) was used for the example presented here.

SIP arithmetic offers several advantages over Monte Carlo simulation, such as

- There is no need to model the distribution with a closed formula, thus the potential errors associated with fitting a distribution to the data can be eliminated
- The calculation time is significantly reduced
- The progression of the calculations can be followed and monitored

The process is illustrated below by using a rutting deterioration model developed for Australian conditions (4). The rutting model was partly based on LTPP observational data from selected arterial road segments of sealed unbound granular pavements. The observational data was combined with accelerated pavement testing (APT) experiments separately examining the impact of increased axle load and various surface treatments on pavement deterioration.

The resulting deterministic rutting model predicts cumulative rutting deterioration with increased pavement age, traffic load, climate, pavement strength and maintenance input. The rutting model has the facility to be converted to an annual incremental model when the traffic load is growing annually.

Input Data

The rutting model was converted to accommodate SIPs whilst maintaining the deterministic model without any constitutional change. To illustrate the process, three uncertain variables, the Thornthwaite Moisture Index, the pavement strength and the annual maintenance input (in terms of \$/lane-km/year) were selected whilst the other input parameters were kept the same as for the deterministic model. The averages of the data were used in the control deterministic model.

The SIP of Thornthwaite Moisture Index (TMI) was calculated from 50 years of monthly rainfall and monthly average temperatures (Figure 4). The initial structural number indicating the pavement's strength (SNC_0) immediately post construction was generated around a measured value, using an assumed distribution based on previous experience with a peak value at 3.5. The annual average maintenance cost (*me*) was derived from 70,000 data points relevant to the network modelled (Figure 5).

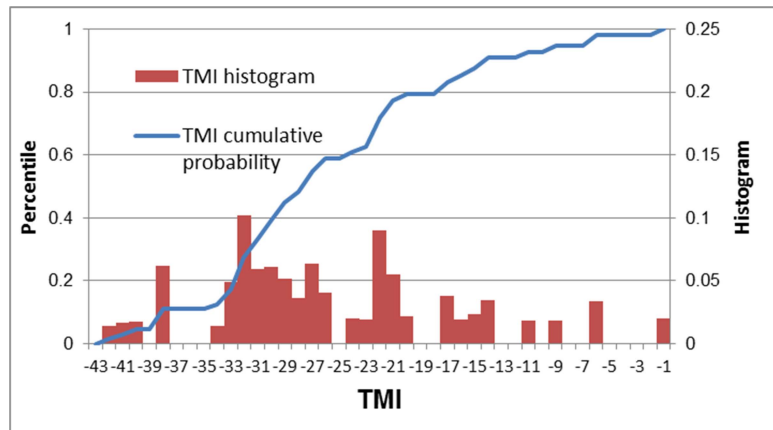


FIGURE 4 Thorntwaite Moisture Index (TMI).

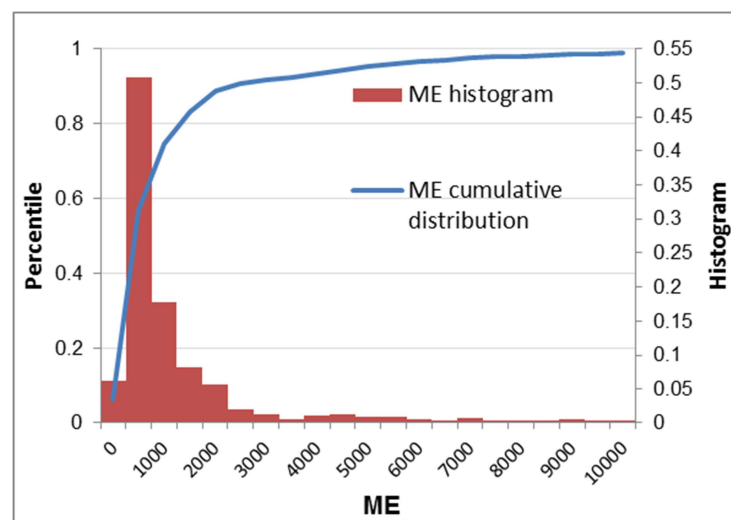


FIGURE 5 Annual maintenance cost (\$/km).

The deterministic models were converted to working with SIPs, using appropriate functions (7) developed as Excel add-ins. SIP operations require that all SIPs have the same length, i.e. the same number of components. Some data, such as the TMI and maintenance cost had to be reduced and others, such as the rutting had to be resized to ensure uniform length. The sequence of the SIP array is critical only if the SIP(s) in the calculations are somewhat correlated. The degree of correlation is irrelevant, the only fact that matters is if the SIPs are paired. For example, deflection and temperature are related, so the sequence in the two data sets must be maintained. In the current example it was assumed that all SIPs represent independent data.

DISCUSSION AND RESULTS

The results of the modelling of rut depth development over a period of ten years are shown in Figure 6. The first year represents the measured data; the subsequent years' graphs illustrate the changing rutting distributions. The slope of the cumulative rut depth histograms display a slight increase, i.e. indicate that the proportion of the worst rutting is increasing. The forecast distributions obviously reflect the deterministic model used as well as the input distributions.

Kadar, Martin Baran and Sen

The comparison of using SIP arithmetic with conventional discrete input using the same model (Figure 6) shows that the conventional ('deterministic') results deviate from the 50th percentile. This is not unexpected, as the deterministic model is the result of curve fitting to data and therefore is an aggregated and simplified representation of the changing data distribution. The results highlight that 'on the average, averages are wrong' (1). The fact, that the results of the deterministic model do not even stay within the range of the distribution forecast on the long run, highlight the shortcoming of deterministic modelling. Operations with SIPs (distributions) will always result in a new distribution. The shape of the new distribution will depend on the shape of the input distributions and the nature of the operations, hence any assumption of symmetrical or bell shape curve may be ultimately illusory. However, the magnitude of the difference between the stochastic and deterministic modelling may vary.

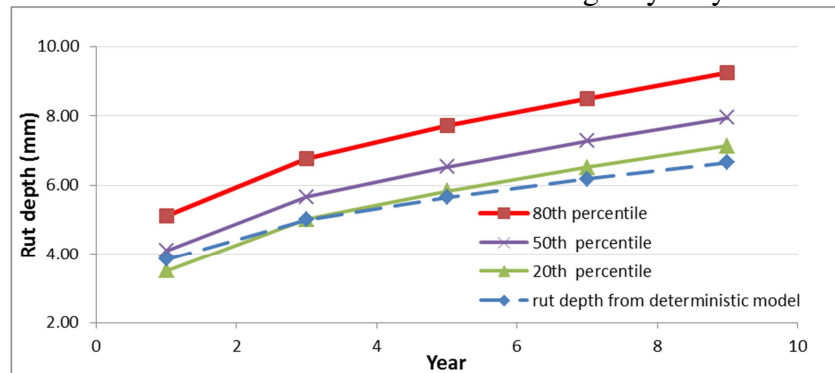


FIGURE 6 Comparison of deterministic and SIP models.

The SIP calculations do not utilise random numbers and therefore the results are repeatable, i.e. they will be the same every time. In one sense this makes the calculation deterministic as nothing random is involved. Probably this is the most significant difference between the principles of Monte Carlo simulation and SIP operations.

Modelling with SIPs utilises the data as is. The only allowed modification of the data is resizing, i.e. increasing or reducing the number of data points to a sufficiently large one, typically 1000-2000 units, without changing the shape of the data distribution. Thus the shape of the distribution is truthfully represented in all cases, unlike in the Monte Carlo simulation where a statistical function must be fitted to the data. Previous work (3,7) indicated that whilst this is possible for some data sets, it is not feasible for practical, industry strength application.

Work to date indicated that the forecast distributions are sensitive to the sequence of the SIP data. This sensitivity may be counterbalanced by the fact that the forecast covers a range with quantifiable certainty and risk level. In the case of the rutting example (Figure 7), the 50th percentile increased to about 8 mm, but 10% of the pavement section had rutting in excess of 10 mm. This allows budgeting for the real treatment length as opposed to budgeting for the whole length based on the average rut depth forecast.

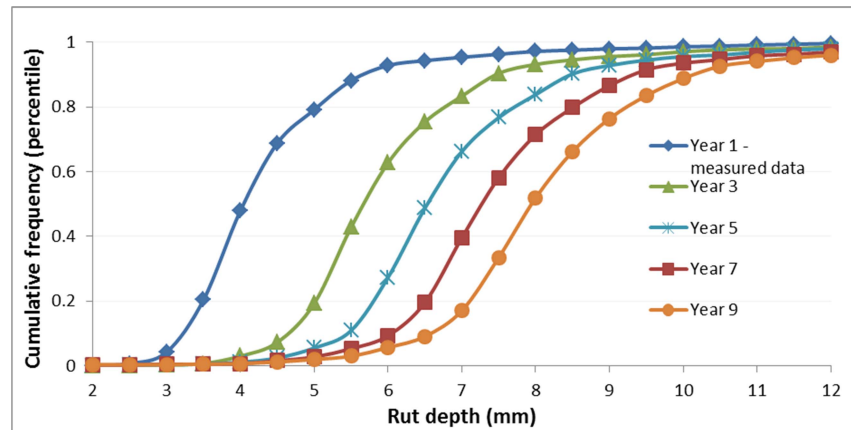


FIGURE 7 Rut depth distribution over the analysis period.

SUMMARY AND CONCLUSIONS

The method and practical implementation of modelling using the full data distribution was demonstrated. The full implementation of the method into a PMS system is currently being undertaken.

The investigation to date has indicated the potential benefits and feasibility of effectively dealing with uncertain variables for forecasting pavement performance and condition. By taking the uncertain nature of selected variables into account, the reliability level and risk associated with the results can be accurately quantified. This is critical e.g. for contractors bidding for maintenance contracts, as the probability of completing the contract within the budget can be determined, or the cost associated with the acceptable risk level can be calculated.

Road agencies will also enjoy similar benefits as the risk level associated with the funding will be known in advance. Road agencies may be able to report the probability to achieve the target level of service with the allocated. The example used in this paper indicated that even the 50% chance of meeting target LoS can be an optimistic assumption.

The technologies utilised and very briefly described here have been developed in the last 10 years. The data condensation technology opens exciting opportunities in data collection, storage and analysis. As large quantities of data can be stored in relative small space, the full data set can easily be stored, transported and utilised.

The relatively simple SIP operations open the road for solutions so far available only to the statistically savvy. Cost estimates, project management, quality control, quality assurance and in general all engineering calculations where currently averages are used as input, can be replaced with the techniques briefly described here.

Probably the most significant outcome of the investigation is the recognition of the need to maintain and preserve the full information contained in the data. Many organisations collect data on unit rates, project costs, etc., but only store permanently an aggregated or summarised version of the data. The lack of appropriate tools leads to losing the information in its fullness or partially due to reduction to average values. The storage and full use of the collected data, without any distortion, results in improved infrastructure management practices by providing forecasts with known reliability and risks. Decisions regarding infrastructure maintenance, and in general regarding any investment, based on known risk level and reliability will contribute to successful and effective infrastructure management.

REFERENCES

1. Savage, S.L. 2009, *The Flaw of Averages: Why We Underestimate Risk in the Face of Uncertainty*, Wiley, Kindle Edition.
2. Paterson, W. and Scullion, T. (1990) *Information Systems for Road Management: Draft Guidelines on System Design and Data Issues*. The World Bank, Policy Planning and Research Staff, Infrastructure and Urban Development Department.
3. Austroads 2013, *Probabilistic road deterioration model development*, Austroads publication AP-T257-13, Austroads, Sydney, NSW.
4. Austroads 2010a, '*Interim network level functional road deterioration models*', Austroads Publication AP-T158/10, Austroads, Sydney, NSW.
5. Austroads 2010b, '*Predicting structural deterioration of pavements at a network level: interim models*', Austroads Publication AP-T159/10, Austroads, Sydney, NSW.
6. Thibault, M 2013a, *Calculating uncertainty*, marc@smpro.ca
7. Kadar, P., Martin, T., Choumavong, L., Baran, M., *Incorporating uncertainty in pavement performance modelling*, 26th ARRB Conference, Sydney, 2014.
8. Thibault, M. 2013b SDXL Reference Manual, CreateSpace
9. Hubbard, W.D. 2010, *How to measure anything*, Wiley.