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# Challenges faced in formulating pavement distress prediction models

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## Abstract

Pavement distress prediction models (PDPM) are normally sought as one of the tools in pavement management systems (PMS). These tools attempt in line with modelling method deployed to capture the progressive nature of pavement surfacing layers' distress as dependent parameter versus causative parameters which serve as independent parameters.

The process of formulating PDPM faces a number of challenges which affects its accuracy in prediction of future state of distresses in question, and hence its effectiveness as a tool for managing road pavements. The list of challenges to overcome is long, but can be categorised in terms of behaviour and characteristics of independent and dependent variables.

Based on the study carried out in Iringa region, Tanzania, the paper looks at challenges noted in an attempt to answer questions such as which variables stand out as most appropriate in reflecting the dynamic nature of pavement distresses so as to serve as dependent or independent variables. Answers provided may serve to improve the formulating process and reliability of PDPM.
*Keywords: pavement distress prediction models, variables, dependent and independent parameters, gravel loss, trend, maintenance, pavement management system.*

## 1 The need for formulating pavements distress prediction models

PDPM are employed to quantify the trend of distress in question as a function of traffic, road geometry, material properties, and climate. The prediction of the expected road distress is of utmost importance for PMS [1].

The models for predicting the occurrence of pavement distress are critical in selecting the optimal remedial schedule for effective PMS. For a management model, the life-cycle of roads pavements can be depicted by the measurements of the trends of distress over time (as shown in Figure 1) [2].

Knowing a unique progression rate of pavement distress is the key to a correct and optimum decision during its conservation cycle [3].

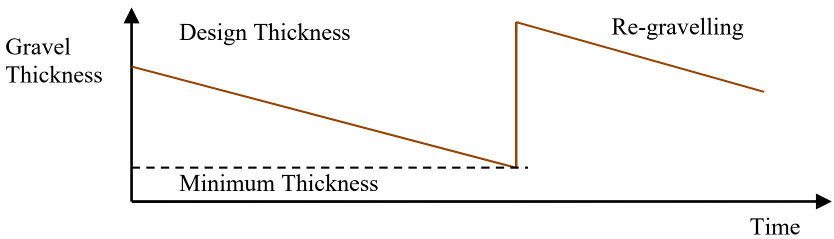


Figure 1: Trend in reduction of gravel wearing course thickness (source: [2]).

### 1.1 Problem statement

PDPM cannot be transferred from one geographical location to the other without affecting their relevance. The parameters which limit such transferability vary within themselves and location, such as climatic condition; terrain; material characteristics and weathering; road user behaviour; quality of construction and maintenance; and traffic type, volume, and loading.

A number of authors on roads pavement performance, agrees that most existing international PDPMs are unable to cope with local variability in materials and climates in predicting changing conditions of pavement distresses. One of these is Uys [4], who pointed out that international gravel loss prediction models which were used in South Africa by then, resulted in a poor estimation of gravel loss, and consequently, inaccurate estimation of the amount required for re-gravelling and unreliable design input for gravel layer thickness requirements as indicated in Figure 2. This was due to the effect of improved construction techniques, where more emphasis on better material selection and stringent quality control measure has been put into place.

The negative effect of the distress model prediction error, which is increasing the cost of PMS, is being expressed further by Madanat [5] of Purdue University in the USA.

Furthermore, the results of work carried out by Paige-Green and Visser [6] showed the danger of using pavement performance prediction models developed in different environments. GEIPOT and UNDP [7] stress that PDPMs must reflect the conditions to which they are applied and must either be developed from local data or modified and verified based on such data.

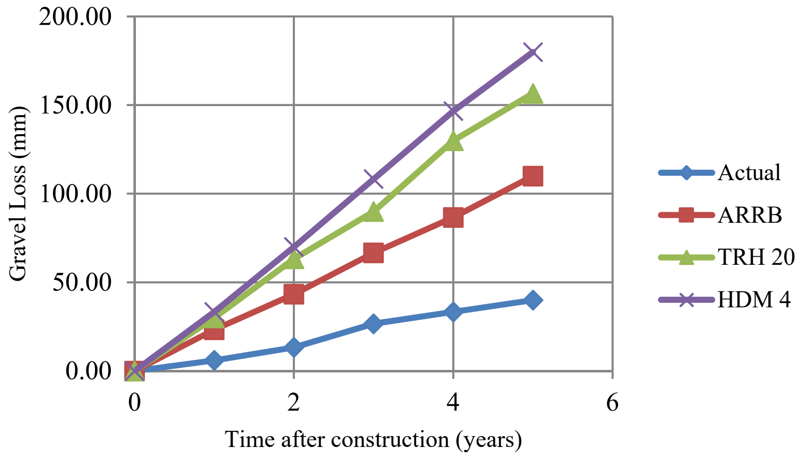


Figure 2: The effect of improved quality in construction and the level of gravel loss prediction (source: [4]).

## 2 Model: a variable entity

A variable is anything that can take different values over a period of time reflecting changes in behaviour as observed. Thorne and Giesen [8] maintain that it is only through observing empirically the way distress vary that one can capture relationship behind the variation, and hence the model.

Austin and Burns [9], and Gichaga and Parker [10] define a model as a simplified representation of reality. The *Advanced Learner's Dictionary of Current English* [11] defines a model as a "simple description of a system, used for explaining how something works or prediction of what might happen"

### 2.1 Model types and classification

Models can be grouped into two types, namely probabilistic and deterministic models [12]. Probabilistic modelling is any form of modelling that utilizes presumed probability distribution of certain input assumptions to calculate the implied probability distribution for choosing output metrics, whereas the deterministic model is a mathematical model in which the outcomes are precisely determined through known relationships among states and events, without any room for random variation [13].

There are different criteria that rule, classification of models; among them are purpose, perspective, degree of abstraction, and content. Classification according to purpose takes into consideration the uses to which models can or shall be put. Planning and prediction models improve the decision-making acumen of managers and represent the two most widely employed purposes to which models can be put into use by road agencies [9].

### 2.2 Characteristics and requirements of an ideal distress prediction model (DPM)

In the DPM all aspects of the real situation irrelevant to the purpose of the model, are ignored in order to maximize the viability of the selected model.

According to Gichaga and Parker [10], during formulating DPM one must ensure that it meets the ideal characteristics as briefly explained in Table 1

Table 1: Characteristics and requirements of ideal DPM (source: [10]).

| Characteristics | Requirements |
|---|---|
| Relevance | Responds to the questions and concerns of the day and of the foreseeable future. |
| Validity | Exhibits trends in the dependent variable that is consistent with pavement engineering judgement and expectations. |
| Accuracy | Confidence that the model estimate is within a certain percentage of the true value. |
| Testability | Results should be verified in the real locality and be feasible to use in the environment of the application. |
| Feasibility | Time, effort and resources required to run the model have to be optimal. |

## 3 Natural road building material essence contributing to its characteristics and evolution of pavement distress

According to McKinlay [14], the characteristics and behaviour of natural building materials depend on the: (i) parent rocks from which they are derived; (ii) type and rate of weathering of these rocks and the resulted soil at its various stages of formation; (iii) means of transport bringing the soil to its present location; (iv) manner of deposition of the soil; and (v) history of loading, drainage, wetting and drying. These modes of natural road building materials formation influence to a great extent, the characteristics and the performance of roads pavement and hence the distress evolution.

## 4 Significance of pavement distress prediction model (PDPM)

A PDPM is a distress specific performance model that can be used to reliably predict pavement performance. Pavement performance is related to the interaction between traffic, the environment and material properties. According to Paige-Green [1] the prediction of the expected pavement distress is of utmost importance for: unsealed or sealed road design, addressing construction short falls and maintenance planning. Prediction of when road pavement condition is likely to need remedial measure is precious information during budgeting sealed or unsealed roads routine or periodic maintenance. Dierks [15] insists that the importance of PDPM is in establishing an economically defendable remedial cycle and setting trigger values for sealed or unsealed road maintenance or improvement. Without establishing the relationship between pavement distress and their causative parameters, it is difficult to set appropriate standards or to know the effect of applied standards on performance [16] so as to address the shortfall. According to The United Republic of Tanzania, Ministry of Works (TZ-MoW) [17] the road wearing surface needs to be maintained periodically throughout the service life of a road in question at a rate dependent on the trend of distress. Hence, pavement deterioration should not be looked at as a shortfall, but as one of the characteristics of road pavements as a result of its interaction with vehicles passage and climatic condition [18].

Furthermore, Henning *et al.* [19] and Ellis [20] assert that the importance of PDPMs is in: i) Facilitation of the understanding of the interaction between the climate, traffic and local materials, which can assist in better planning of maintenance activities for the short, medium and long-term period; ii) Attaining appropriate pavement materials standards and specifications for local condition, and improving the same; iii) Assisting in prediction of the annual expenditure on routines and periodic maintenance the road in question will receive each fiscal year; and iv) Providing a better understanding of the behaviour of natural road building materials within a region so that a number of measures can be applied during design and construction phases to reduce the rate or delay the start of the deterioration of the sealed or unsealed roads in question.

### 4.1 Attributes to the failure of international PDPMs deployed locally

The start and rate of pavement distresses are influenced by a number of factors, such as road geometry and location, material quality and quantity, traffic volume, type and loading, climatic conditions, construction standards and maintenance practices [20]. These factors vary from time to time and if not addressed might be the source of the failure of PDPM. Major reasons why PDPMs, which are used internationally, may fail are:

- Models becoming obsolete. It should be noted that performance prediction models cannot go beyond the limitations of the standards and technology which developed the data that fed them [21].
- Pavement behaviour, which is defined as the function of the condition of the pavement with time (National Institute of Transport and Road Research (NITRR) [22]. It is worth to note that each pavement segment or section is unique and careful monitoring is needed to establish its behaviour patterns.
- Challenges in capturing and addressing the local characteristic variation within the same source and type of natural materials.
- The difference in the history of soil formation process affects the performance of the natural materials in different regions. For example, laterites developed by chemical decomposition occur predominantly in Brazil, and soils resulting mostly from physical (mechanical) disintegration or arid pedogenesis predominate in Southern Africa. These differences in soil formation process may account to a large extent for the differences between the progression rates of pavement distress experienced in different regions [23].

- Greater variability of marginal materials' physical properties, quality of construction and large fluctuations in traffic volume, composition and vehicle loading that are typically encountered in sub-Saharan African countries [20].

According to Harral and Faiz [24], even the standard engineering practices on road pavements construction have different effect in different environments, hence performance. This stress furthers the needs of PDPM to be tailored to suit local characteristics.

# 5 Modelling

Modelling of pavement deterioration trend provides the tool to predict how a pavement condition will turn into even for the most complex situations. It provides quantitative information on the achievement of design and subsequent maintenance methods applied, assess interaction of various parameters affecting the distress in question, and predict statistically accurate the life-cycle of road pavement, thus reducing risk of pavement not meeting the anticipated design life with optimum maintenance and enabling future management of asset to be planned effectively.

In this study the modelling of pavement distress was geared in coming up with gravel loss prediction model (GLPM) for Iringa region in Tanzania.

## 5.1 Variables for formulating the gravel loss prediction model

According to Henning *et al.* [25] there are many independent variables to be concerned with during modelling GLPMs which contribute to gravel loss (GL) as dependent variable. The number of independent variables contributing to GL is considerable, some of these which were tested during this study are average daily traffic (ADT), average annual rainfall, grading modulus (GM), grading coefficient (GC), shrinkage product (SP), gravel materials passing through a 37.5 mm-sieve, and plasticity factor (PF). Others are gravel materials passing 2.00, 0.425, and 0.075 mm-sieves, liquid limit (LL), plasticity index (PI), shrinkage limit (SL), and road longitudinal gradient (Grad), dust ratio (DR), plasticity modulus (PM), plasticity product (PP), coarseness index (CI), and gravel material's geology. Derived parameters are grading modulus (GM) and plasticity factor (PF). GM was calculated from particle size analysis results of gravel materials used for surfacing the gravel roads under study, while PF was derived from the product of percentage of fine component of gravel materials passing through a 0.075-mm sieve and plastic limit (PL).

Among all these parameters only six were found to be significant to be employed in the GLPM.

## 5.2 Gravel loss modelling approach

The basic framework for analysing the determinants of a GLPM in this study was a panel data regression model of the following form in eqn (1) as adopted from Greene [26].

According to Cameron and Trivedi [27] the best method to obtain a consistent estimator is to use a population average (PA), as both fixed effect method (FEM) and random effect method (REM) are best under strict exogeneity of the explanatory variables. PA states that the expected value of the distribution of GL (dependent variables) is functionally related to independent variable. In simple terms, it tells how the average response of GL varies with independent variables. Thus the final gravel loss prediction model was based on PA, and took the form shown in eqn (1).

$$\boldsymbol{GL_{it} = \beta_0 + \beta_1 ADT_{it} + \beta_2 PF_{it} + \beta_3 DR_{it} + \beta_4 PM_{it} + \beta_5 PP_{it} + \beta_6 Di + \varepsilon_{it}} \quad (1)$$

where: $GL$ is gravel loss, $ADT$ is the average daily traffic, $PF$ is the plasticity factor, $DR$ is dust ratio, $PM$ is plasticity modulus, $PP$ is plasticity product, $D_i$ is a dummy variable for climate. i = 1 if the road is located in a wet climate, i = 0 otherwise, $\varepsilon_{it}$ is the error term, $\beta' i$ are parameters, and $i$ and $t$ index road test section and year respectively.

The study was based on prediction of gravel loss, implying that all independent variables employed in the prediction model influence to a certain degree gravel loss from gravel surfaced unsealed roads. The relationship between dependent and independent variables can either be linear or nonlinear, but in this study it was assumed to be linear. The $\beta_n$ are impact parameters, indicating the degree by which GL changes given a one unit change in the corresponding variables. The signs of parameters accompanying variables in the prediction model eqn (1) should behave in line with the parameter's influence on gravel loss. The following are the hypothesized signs of parameters.

The parameter $\beta_1$ should take positive sign indicating that the unit increase in ADT will trigger unit increase in GL. PF is the product of percentage of fine component of marginal materials passing through a 0.075 mm-sieve and PL. PM and PP are the product of percentage of fine component of marginal gravel materials passing through a 0.425 and 0.075 mm sieve respectively and PI. DR is the quotient of percentage of fine component of marginal gravel materials passing through a 0.075 by 0.425 mm sieve. From the forgone definition, it is clear that the variables PF, PM, PP, and DR describe the physical state of marginal gravel materials. The rate of gravel loss varies with the change of physical state of marginal gravel materials. Taking PL and PI constant, the increase in PF signifies decrease in GL (i.e. traffic induced GL is less as the coarse fraction decreases). In this case $\beta_2$ should take negative sign. $\beta_3$ should take positive sign as an increase in DR signifies an increase in GL. The effect of PM and PP to GL is similar to PF, hence $\beta_4$ and $\beta_5$ should take negative sign. $\beta_6$ should take negative sign as the GL in wet climate (which is represented by D1) is less than in both dry and moderate climate

### 5.2.1 Correlation coefficient analysis

A correlation coefficient indicates the strength of a relationship between two or more variables [28]. Table 2 shows the correlation between the variables used in formulation of the GLPM.

The correlation between variables may be positive, negative, or zero. When the correlation is positive, the variables tend to be both high or be both low. When the correlation is negative, one tends to be high and the other low [29]. As shown in Table 2, only the average daily traffic has a positive relationship with GL.

Table 2: Correlation between the variables used in formulation of the GLPM.

| Variables | GL | ADT | PF | DR | PM | PP | D1 |
|---|---|---|---|---|---|---|---|
| GL | 1.0000 | | | | | | |
| ADT | 0.0264 | 1.0000 | | | | | |
| PF | -0.3367 | -0.0495 | 1.0000 | | | | |
| DR | -0.1835 | 0.0444 | 0.6556 | 1.0000 | | | |
| PM | -0.3479 | -0.1461 | 0.8225 | 0.5297 | 1.0000 | | |
| PP | -0.2735 | -0.1170 | 0.8428 | 0.7837 | 0.9259 | 1.0000 | |
| D1 | -0.4400 | -0.2200 | 0.3019 | -0.1006 | 0.3484 | 0.1604 | 1.0000 |

All other variables show negative relationship with GL. Correlation coefficient does not distinguish independent from dependent variables, and is not affected by changes in the unit of measurement of variables [30]. The existence of a strong correlation does not imply a causation effect. It only indicates the tendencies present in the data [29].

Table 3: Regression results for random effect, population average and SPSS.

| Variables | Random effect | Population average | SPSS |
|---|---|---|---|
| ADT | 0.000000897 | 0.000000694 | 0.0000159 |
| PF | 0.0000268 | 0.0000135 | -0.001 |
| DR | -0.127*** | -0.124*** | -0.121*** |
| PM | -0.0174*** | -0.0169*** | -0.023*** |
| PP | 0.000236*** | 0.000229*** | 0.0002*** |
| D1 | -0.0142 | -0.0144* | -0.014** |
| Constant | 0.115*** | 0.113*** | 0.127*** |
| N | 66 | 66 | 66 |

Notes: *** denotes; significant at 1%, ** significant at 5%, and * significant at 10%

### 5.2.2 Estimated gravel loss prediction model

The estimates' results in Table 3 column three are summarized by the regression eqn (2).

$$GL= [0.113+0.000000694\ ADT+0.0000135\ PF- 0.124DR - 0.169PM +0.000229PP-0.0144D_1]\ mm \tag{2}$$

where GL is the annual gravel loss in mm, ADT is average daily traffic in both directions, PF is plasticity factor in percentage, DR is dust ratio, PM is plasticity modulus in percentage, PP is plasticity product in percentage, and $D_1$ is a dummy variable which represents climatic condition. $D_1$ = wet climate, and $D_0$ = dry or moderate climate.

### 5.2.3 Interpretation of the results

From Table 3, Variables DR, PM, PP are highly significant at 1% significance level, whereas climatic dummy variable (D1) is significant at 10% level.

The value of the constant term ($\beta_0$) is 0.113 implying that when the independent variables ADT, PF, DR, PM, PP and $D_1$ are not contributing to gravel loss, the loss will be equal to 0.113mm. This can be attributed to variables not related to those addressed by an error term, such as erodibility characteristics of soil and weathering effects. The ADT and PF parameters are not significant in explaining the GL, but their presence is vital so as to avoid bias due to omitted variables. It is noted further that GL decreases by 0.124 mm and 0.0169 mm for each unit increase in DR and PM respectively. However, GL increases by 6.94 x $10^{-7}$ mm, 1.35x$10^{-5}$mm, and 2.26 x$10^{-4}$ mm for every unit increase in ADT, PF and PP respectively.

Table 4: The GL analysis of variation.

| Model | Sum of squares | Degree of freedom | Mean square | R square | F Statistic | Significance |
|---|---|---|---|---|---|---|
| Regression | 0.008 | 6 | 0.001 | | | |
| Residual | 0.019 | 59 | 0.000 | 0.300 | 4.112 | 0.002 |
| Total | 0.027 | 65 | | | | |

Except for the signs of ADT, PM and $D_1$ parameters which tally with those hypothesized by the study, the signs for PF, DR, and PP did not tally with those hypothesized. These differences in signs do not invalidate the model, but only tells the direction of relationship between dependent and independent variables.

Gravel roads located in wet area experiences a GL of about 0.0144 mm less than the roads located either in moderate or dry areas if all other factors remain constant. The GL is statistically significant at 1% and its coefficient of determination ($r^2$) is 0.3 as shown in Table 4. From Table 4 it is noted that, the model is statistically significant at 1% and coefficient of determination ($r^2$) is 0.3.

## 6 Statistical significance

A significance test is a procedure by which sample results are used to verify the truth or falsify a null hypothesis [30]. It is based on a test statistic that indicates whether or not the data set give evidence against the null hypothesis. The actual probability of obtaining a value of the test statistic is termed p-value (probability value) which is defined as the lowest significance level at which a null hypothesis can be rejected [31]. Significance in statistical sense implies that the evidence against the null hypothesis has reached the standard set by α [30]. If the p-value is as small as or smaller than α, we say that the data are statistically significant at level α [30], otherwise it is not significant. Thus a formulated gravel loss prediction model depicted in Equation 2 is statistically highly significance at 1% level, as p which is equal to 0.002 is less than α at 1% level.

### 6.1 Coefficient of determination ($r^2$)

The coefficient of determination ($r^2$) measures the proportion of variation in gravel loss that is explained by the independent variables in the regression model [31]. $r^2$ is fundamentally a property of the linearity of the data, it measures how well the regression line predicts the data [21]. $r^2$ will always lie between 0 and 1 no matter what the units of dependent variable may happen to be. According to Schmidt [21] there are regressions with very high $r^2$ but very poor estimates of parameters, and conversely, there are regressions with very low $r^2$ but with excellent estimates of parameters.

Schmidt [21] is of opinion that dependent variables which has many explanatory variables are hard to predict as they have very large error terms and residuals, which results in small $r^2$**.** It is thus expected that pavement distress prediction models will have many explanatory variables and consequently relatively low regression coefficients. This was the case with Brazilian [32] and New Zealand [19] GLPMs Equations, which had the $r^2$ values of 0.313 and 0.34 respectively. From the above discussion, it follows that the GLPM formulated by this study can be used to predict the trend of gravel loss for Iringa region condition in-spite of its low $r^2$ [33].

## 7 Conclusions and recommendations

### 7.1 Conclusions

- In general no PDPM can capture all independent variables contributing to the distress in question; however, thoroughly study on the pavement performance will enable key variables behind distress evolution and its trend to be identified.
- PDPM is effective when accompanied by an effective PMS; otherwise as the wearing course performance is progressively diminishing, distress developments will accelerate beyond the model's predictive capacity.
- It should be stressed here that the uses of a PDPM developed in the context of different environments economically and politically will not address the local condition.
- The number of parameters encompassing pavement performance influences significantly the modelling process, particularly regression coefficients which normally range between 0.3 to 0.5.

### 7.2 Recommendations

- PDPM to become an effective and efficient tool in PMS, it has to be dynamic and reflect local material characteristics, climatic changes, and changes in road pavements design, construction, and maintenance technology.

- It is imperative that the survey team, equipment, frequency of surveys, and methods of collecting and analysing data to be used for formulating a PDPM must be consistent to be valid. Furthermore, it has to be compatible with a distress in question.
- The rate of pavement distresses evolution reflects the quality of construction/maintenance and characteristics of natural materials employed as wearing course, hence it can be employed as a quality assessment and auditing tool.
- Changes in road user behaviour associated with the vehicles' technological innovation and the effect of vehicles' manoeuvres resulting in shearing movements of granular wearing course materials have to be independently studied and its effect and significance noted during modelling exercise.
- The effects of errors arising from PDPMs affects timing of remedial measures and strategic planning of materials sources, hence it is imperative that the accuracy of the formulated distress prediction models be verified periodically.
- PDPMs reflect the conditions during the period in which the data were collected and processed to obtain the prediction model in question. Predictions will be valid as long as those conditions persist, changes in any one of those conditions will necessitate new model. Hence the view that such model has to be dynamic.
- Implementing a newly locally formulated PDPM as part of PMS for most sub Saharan African countries road agencies is far from being reality and will remain an academic exercise until there are government commitment, management ability, adequate appropriate staff, accountability, and incentives.

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