Seemingly Unrelated Regression Equations for Developing a Pavement Performance Model

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Abstract

The paper presents a joint analysis of some pavement performance indicators based on a system of seemingly unrelated regression equations (SURE) which allows to handle correlated error terms. In particular, three major indicators such as the side friction coefficient (SFC20°C), mean-profile depth (MPD), and international roughness index (IRI), were measured in a case study and subsequently used in analysis. Regression parameters were estimated by the Maximum Likelihood Method and the t-statistic was considered to show the statistical significance of regression coefficients. The results show that estimation points have the signs expected: the $SFC_{20°C}$ decreases as the number of accumulated trucks (N_t) increases; whereas the MPD and IRI increase as the number of trucks increases. A likelihood ratio test was also carried out to determine whether the system model, which assumes correlation among error terms, was more appropriate than separate models. In this particular case, with three degrees of freedom, was found that the result corresponds to a p-value 0.150 and the null hypothesis cannot be rejected at any significance level less than this value.

1. Introduction

Physical measures of road conditions are often used as a basis for determining safety needs, rehabilitation requirements and resource allocation. For Italian motorways, among various pavement-functionality measures, the Sideway Force Coefficient (SFC), the International Roughness Index (IRI), and the MPD (Mean Profile Depth) are parameters that play a significant role for forecasting the performance of a pavement over time.

The SFC is used to describe the friction between the vehicle tyre and pavement. It is defined as the ratio between the tangential force divided by the normal force at a standard speed. This parameter is expressed numerically by positive values smaller than 1 (or smaller than 100 in some official reports where its value has been multiplied by 100). The SFC is generally thought to be above all associated to road safety.

The IRI is used to describe a characteristic of the longitudinal profile of a travelled wheel track. It is based on the ratio of a standard vehicle's accumulated suspension motion divided by the distance travelled by the vehicle during the measurement. The IRI, which is expressed in m/km (or mm/m), is generally considered to be a standardized roughness measurement that is correlated more especially with vertical passenger acceleration (a measure of ride quality).

The MPD, which is a measure of the macrotexture of pavement surface evaluated by means of a laser, is generally expressed in mm and appears to influence in particular tire and road noise, as well as friction.

The aforementioned three measures of pavement performance are often thought to be correlated to each other. For example decreases in sideway force coefficient are usually considered to be accompanied by increases in international roughness index and/or increases in the mean depth of texture profile. Additionally, it is to be said that different indicators when are used separately capture only one aspect of the performance of a pavement. The need to show the interrelation among different indicators while accounting for the full performance of a pavement over time have stimulated researchers in the development of interesting statistical models, which is

within the scope of this paper.

A wide range measures can be found in the international literature to evaluate pavement condition, such as more especially: (i) friction, (ii) roughness, (iii) rutting, (iv) fatigue cracking, (v) surface deflection. In addition numerous methodologies have been used to account for the pavement performance over time. However, the majority of these studies, which are generally based on regression models that correlate the dependent variable (performance indicator) to explanatory variables (typically including traffic, weather conditions and/or structural strength), consider only a performance indicator or each performance indicator investigated is assumed in analysis to be unrelated to other ones. In keeping with the studies of last decade, for example, Loprencipe & Cantisani (2013) apply an unified analysis both for surveys and processing of acquired data with the aim to represent the pavement surface characteristics. Archilla & Madanat (2001) use a methodological approach based on a joint estimation that combines the information from two different data sources in order to develop a rutting model of pavement. Prozzi & Madanat (2004), involve the multivariate regression for combining experimental and field data to predict pavement roughness progress. Cantisani & Loprencipe (2010) investigate on the correlations between roughness and road users' comfort. Archilla (2006) proposes a rutting model that is a modification from the one presented by Archilla & Madanat (2001). In particular they apply a methodological approach which allows some model parameters to vary randomly, in contrast with the assumption that parameters are constant across observations. By using this methodology they find different results from other simpler models that ignore the unobserved heterogeneity or attempt to capture it through a mixed-effects approach. In this respect, it is to be remembered that a mixed-effects approach is a combination of fixed and random-effects where only the model intercept is allowed to vary randomly, while the other parameters are fixed in model (see Hilbe, 2007; Greene, 2003; Greene, 2007; Caliendo et al., 2015; for greater in-depth knowledge about the random-intercept model which is known in the literature to be equivalent to random-effects one). Onar et al. (2006) show that the mixed-effects models are useful in analysing pavement performance from accelerated pavement testing (APT) based on rut depth. Puccinelli & Jackson (2007) combining environmental and structural factors and by using multivariate regression procedures develop individual models of fatigue, rutting, and roughness, respectively. The American Association of State Highway and Transportation Official (2008) in the more recent version method of pavements design, which is known as the Mechanistic-Empirical Pavement Design Guide (MEPDG), also proposes individual models of fatigue, rutting, and roughness. However, the MEPDG requires to designers to recalibrate the coefficients of the distress models depending on local conditions. In this respect, Caliendo (2012) has recalibrated these coefficients for the design of flexible pavements in Italy. Khraibani at al. (2012) use the mixed-effects models for providing an evolution law of pavement deterioration based on cracking. Fini & Parast (2012) use the multivariate regression analysis to compare the effect of some variables (age, temperature, freezing index, and surface thickness) on the progression of pavement roughness. Loprencipe et al. (2015) consider performance parameters to set a global assessment method of road distresses.

Despite the significant contribution to the state-of-the art in pavement performance modelling over time, the aforementioned studies present a limitation consisting more especially in the fact that the proposed models are based on individual performance indicators not correlated to each other. It is to be stressed that one type of indicator does not sufficiently capture the overall performance of a pavement, as a consequence more indicators should be used and these should be jointly involved in regression models in order to fully reflect the progress of deterioration mechanism. With regard to this, Prozzi & Hong (2008) present a statistical approach to jointly account for the performance of a pavement based on two different indicators, such as roughness and rut depth. In particular a statistical regression system is presented to capture the deterioration process in terms of these two indicators considered simultaneously in analysis with correlated error terms. The proposed regression system is currently denoted in the literature as the seemingly unrelated regression estimation (SURE) technique. The SURE approach, which appears to have been originally developed by Zellner (1962), accounts for the correlation among the error terms in each seemingly unrelated equation in order to improve the parameter estimates. In fact, the independence assumption of error terms might not be valid because the indicators describing different deterioration are from the same road section and thus likely to share some unobserved characteristics. Therefore, it is more realistic to incorporate in the analysis the correlation among equations. Greater knowledge about this subject can be found more especially in Wooldridge (2002), Greene (2003), Greene (2007), Washington et al. (2011).

Applications of the SURE technique to pavement performance indicators can be found also in Anastasopoulos et al. (2009), where the fixed-parameters SURE is used for mathematically resolving a system of four pavement condition variables with correlated error terms. Subsequently to the aforementioned paper, Anastasopoulos et al. (2012) make one step further in research by using the random-parameters SURE to account for both the

correlation that exists among pavement-performance measures and the heterogeneity across observations. The unobserved heterogeneity may be due to the fact that information related to factors known to affect the performance measures might not be available in databases. This extension of the SURE technique has been applied to four performance indicators simultaneously considered; such as roughness, pavement condition rating, rut depth, and deflection. More specifics on the random-parameters SURE can be found above all in Singh & Ullah (1974).

Although the use of the SURE approach represents a significant development in research concerning the progress of pavement deterioration over time, the possibility to account for the pavement performance based on the three indicators jointly applied such as the aforementioned SFC, IRI, and MPD taking into account the correlation among error terms does not appear to have been investigated in depth. Additionally, it is to be said that local input data for traffic, climate, and materials, which in Italy are different from those used in studies of other countries, do not seem to have been hitherto implemented in the SURE technique. There is an a priori reason for believing that the transferability of results to a geographic area different from that in which the results have been obtained may present problems because they are based on local conditions that are different from those of the place that is being studied. Moreover, it is to be said that the use of asphalt porous instead of traditional bituminous mixture in the surface layer of pavement has not yet been sufficiently investigated. As a result, there are at least three reasons to justify this paper. The first is motivated by the need to use the SURE technique to pavement performance considering that the contemporaneous measurements of the SFC, IRI, and MPD might be affected by correlated error terms. The second is for applying this technique to local conditions. The third is for showing the results when a porous asphalt is used.

In the light of the previous considerations, the main objective of the current paper is to make an additional development to the state of knowledge by applying the SURE technique at Italian conditions. For this purpose the paper is organized as follows: the next section contains the description of the data set of a case study regarding an Italian motorway section. In particular the SFC, IRI and MPD indicators are measured on a porous asphalt pavement over time. The third section presents the statistical methodology used. Then the results are presented and discussed. Finally the conclusions and directions for future research are reported.

2. Data Description

The monitored motorway, which is a four-lane median-divided road, is located in the South of Italy, connecting the cities of Salerno and Reggio Calabria (marked as the A3 motorway). Three performance indicators of pavement known as the side force coefficient (SFC), the international roughness index (IRI), and the mean profile depth (MPD) were more especially measured in three different time periods on a same section of this motorway. For this aim, the ERMES (Equipment for Routine evaluation of Macro-texture, Evenness and Skid resistance) was used. The ERMES, which is a SCRIM (Side force Coefficient Road Inventory Machine) plus a multifunctional equipment, is an instrumented vehicle that travels on the road at a standard speed (60 km/h) for surveying simultaneously the three aforementioned performance indicators. Since these indicators are measured contemporaneous by the same machine, the correlation among error terms might be expected.

The SFC, IRI, and MPD were surveyed in years 2007, 2010, and 2012, on a same road section of the motorway investigated along the direction north of right lane (prevalently interested by trucks). This motorway section is 3.6 km long and its longitudinal position is from the km 32+010 to km 35+610. Longitudinal measurements repeated in the aforementioned three years are used in analysis. The values of these measurements, which are collected every 10 m, were extracted from the official reports of the Motorway Management Agency (MMA). For each data also a variety of details were recorded, including more especially date and spatial location of measurement, as well as pavement temperature. In this respect, it is to be said that a temperature adjustment factor is also applied by the Motorway Management Agency to take into account the effects of pavement temperature on the measurement of the SFC. Then, values of the SFC at a standard temperature of 20°C ($SFC_{20°C}$), which are computed and reported directly in these official documents of the MMA, were more especially used in analysis. With reference to the IRI and MPD, because the values of these indicators might be scarcely influenced by temperature, no adjustment factor is provided by the MMA. In the light of these considerations, the number of observations for each of the three mentioned indicators ($SFC_{20°C}$, IRI, and MPD) measured on the motorway section investigated is equal to 360 for each of the three aforementioned years. Summary statistics of these three performance indicators are given in Table 1.

Table 1. Summary statistics of performance indicators

Year	Sideway Force Coefficient (SFC) at 20°C					Mean Profile Depth (MPD) [mm]					International Roughness Index (IRI)[mm/m]				
	Mean	Mode	Standard deviation	Min	Max	Mean	Mode	Standard deviation	Min	Max	Mean	Mode	Standard deviation	Min	Max
2007	55.34	58.04	3.30	42.56	60.94	1.38	1.38	0.10	0.96	1.62	2.22	1.82	1.29	0.80	9.04
2010	54.51	58.00	4.50	36.00	64.00	1.62	1.63	0.11	1.01	2.58	2.41	1.90	1.39	0.80	8.90
2012	43.72	45.00	3.22	34.00	51.00	1.64	1.69	0.17	0.93	2.39	2.67	2.10	1.00	0.80	7.60

The measurements of these performance indicators resulted to be correlated. Table 2 shows that there is a negative relationship between the SFC20°C and MPD, as well as between the SFC20°C and IRI; whereas a positive relationship exists between the MPD and IRI. This means that to a decrease of friction over time is associated to an increase both of profile depth and roughness; whereas as profile depth increases also roughness increases. Accounting for these correlations is an important concern in selecting of an appropriate statistical methodology.

Table 2. Correlation coefficients of the pavement performance indicators

	SFC at 20°C	MPD [mm]	IRI [mm/m]
Sideway Force Coefficient (SFC) at 20°C	1		
Mean Profile Depth (MPD) [mm]	-0.491	1	
International Roughness Index (IRI)[mm/m]	-0.351	0.206	1

Traffic data and the percentage of trucks were also extracted from the official reports of the MMA. On the basis of the available traffic data, the authors estimated the annual average daily traffic (AADT) for one travel direction at years 2007, 2010, and 2012 that was found to be respectively of 21786; 22324; and 22682 vehicles per day. The percentage of trucks (vehicle weight exceeding 30 kN) was 14.9% for all the three years considered with the 90% of trucks travelling on the right lane only. By assuming as a reference the year 2007, the cumulative number of trucks (N_t) that had travelled on the right lane of the A3 motorway in the north direction only was estimated to be of 2.8×10^6 and 5.31×10^6 at year 2010 and 2012, respectively.

The surface layer of the investigated pavement consists of porous asphalt with a thickness of 4 cm. The average values of porous asphalt characteristics that were tested are as follows: Marshall stability equal to 6.9 kN, indirect tensile strength of 1.95 N/mm^2, volume of air voids equal to 23%, bitumen content of 4.6% by weight. The grading distribution (% passing by weight) of the limestone and basalt mineral aggregate used in the asphalt porous is as follows (in brackets are the sieve sizes in mm): 100% (20), 98.89% (15), 55.12% (10), 14.28% (5), 10.39 (2), 6.37% (0.42), 5.29 (0.18), 4.11% (0.075).

It is to be stressed that the main scope of this paper is to present a procedure for processing the acquired data and from a statistical view point showing the potential of the SURE method. Therefore more detailed information related to SFC, IRI and MPD is omitted to save space.

3. Exploratory Analysis

Given that the longitudinal measurements of the three aforementioned indicators were obtained on the same motorway section but in different times, this needs some questions and assumptions to be discussed before stating the statistical modelling.

When a survey is conducted in a month different from that of the preceding years, this implies that there might be a different amount of time from the last rain during which the pavement is dry. As a result the pavement surface might be cleaner (or less clean) if compared to surface conditions of preceding survey, which might influence the values of measurements even if the pavement temperature is the same. In order to reduce the probability of this type of error, monthly adjustment factors derived from the literature (see Rogers & Gargett, 1991) were used in this paper for the years 2010 and 2012 by assuming as a reference the month (September) in which the surveys was carried out in the year 2007.

Also, when the surveys are repeated in different times, a second concern is that the initial measurement point

might be not exactly the same. For detecting the possible presence of this kind of error and correcting it, we applied a cross-covariance analysis to the available data (for a more in depth knowledge see Yaffee & McGee, 2000; or Shumway & Stoffer, 2011). Given two time series, say, y_1 and y_2 the cross-covariance function is here defined as:

$$\gamma_{y_1 y_2}(l) = \begin{cases} \dfrac{1}{N} \displaystyle\sum_{x=0}^{N-|l|} [y_2(x+l) - \overline{y_2}][y_1(x) - \overline{y_1}], & l \geq 0 \\ \gamma_{y_1 y_2}(-l), & l < 0 \end{cases} \tag{1}$$

where N is the number of points in which the observations have been carried out (in particular, in the present application, observations are taken every 10 m across a 3600 m road section, so as $N = 360$); x denotes the ordered position of points in the series (x proceeds from 0 to 360); l is the unknown parameter that denotes the lag separation between the two time series; $\overline{y_1}$ and $\overline{y_2}$ are the means of the observed values respectively in y_1 and y_2. In order to estimate the lag separation (l) between the two series of spatial data, the aforementioned cross-covariance function was computed and the lag corresponding to the maximum value of this function was used for correcting the aforementioned type of error. Figure 1 shows this procedure for the two series concerning the measurements of SFC$_{20°C}$ in the years 2007 and 2010 (a *lag* = - 10 m was found in this case).
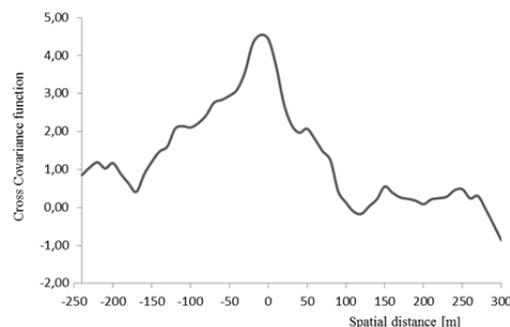

Figure 1. Cross-covariance function vs spatial distance for the SFC20°C time series (years 2007 and 2010)

Another additional question is that the wheel track followed by the ERMES along motorway during a survey might be slightly different from that followed in other years. This might imply, for example, that some measurements may have been carried out in points having lateral positions that are slightly different from those of the preceding surveys. For reducing a possible influence attributable to some lateral position errors on the measurements carried out at different times, the average of SFC$_{20°C}$, IRI, and MPD values over adjacent sections of 50 m each were computed. It is to be said that as far as the authors are aware the road sections investigated did not receive significant actions of maintenance over time. Then, it was not necessary to remove any of them from the analysis.

In the light of the above considerations and assumptions, a number of $N = 72$ observations corresponding to the average values (computed on road sections 50 m long) of each of the three aforementioned performance indicators (SFC$_{20°C}$, MPD, and IRI) for each of the three years monitored (2007, 2010, and 2012) were considered in the statistical analysis.

4. Methodology

Seemingly unrelated regression estimation (SURE) method is used to analyse a number of regression functions with correlated error terms. The SURE method uses the correlation between the error terms of the system of equations to improve upon the parameter estimates.

A system of seemingly unrelated regression equations can in general be mathematically represented in the form as follows:

$$y_{i1} = f_1(\boldsymbol{x_{i1}}, \boldsymbol{\gamma_1}) + \varepsilon_{i1}$$
$$y_{i2} = f_2(\boldsymbol{x_{i2}}, \boldsymbol{\gamma_2}) + \varepsilon_{i2}$$
$$..... \tag{2}$$

$$y_{iM} = f_M(x_{iM}, \gamma_M) + \varepsilon_{iM}$$

where $y_{i1.....}y_{iM}$ = observed performance indicator values; M = number of indicators; i = observation number; N = observations in total; $f_1(.)....f_M(.)$ = function that describe the performance indicator's deterioration; $x_{i1}... x_{iM}$ = explanatory variables vector; $\gamma_1... \gamma_M$ = parameters vector that have to be estimated; $\varepsilon_{i1}... \varepsilon_{iM}$ = error terms. Statistically, it is to be said that there is not direct interaction among the performance indicators. That is, y_{i1} does not directly determine $y_{i2},......,y_{iM}$; and y_{i2} does not directly determine $y_{i1},......,y_{iM}$, and so on. However this method (i.e., SURE) taking into account the contemporaneous correlation of error terms can provide more efficient parameter estimates.

Denoting the errors terms vector as ε_i'= [ε_{i1}, ε_{i2},... , ε_{iM}], the variance covariance matrix of ε_i' is expressed as:

$$\sum = E[\varepsilon_i \varepsilon'_i] = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1M} \\ \sigma_{21} & \sigma_{22} & ... & \sigma_{2M} \\ \vdots & \vdots & \vdots & \vdots \\ \sigma_{M1} & \sigma_{M2} & ... & \sigma_{MM} \end{bmatrix} \tag{3}$$

where σ_{jk} = covariance between the error terms of equations j and k in Equation (2) with:

$$\sigma_{jk} = \frac{\sum_{i=1}^N (\varepsilon_{ij} - \overline{\varepsilon_j})(\varepsilon_{ik} - \overline{\varepsilon_k})}{N} \tag{4}$$

$$\overline{\varepsilon_j} = \frac{\sum_{i=1}^N \varepsilon_{ij}}{N} \tag{5}$$

$$\overline{\varepsilon_k} = \frac{\sum_{i=1}^N \varepsilon_{ik}}{N} \tag{6}$$

It is to be noted that whether the deterioration models based on individual performances indicators are assumed to be separate, this implies that these models are unrelated so that $\sigma_{jk} = 0$ for $j \neq k$ (the off-diagonal elements are equal to zero).

To estimate the above mentioned joint system of equations, the maximum likelihood estimation (MLE) method is used. A likelihood ratio test (LRT) can also be carried out to determine whether the system model that assumes correlation is more appropriate than separate models. In this respect, more detailed information can be found in Greene (2003). Green (2007) has also developed an estimation procedure.

5. Analysis of Results

5.1 Estimation Results

The estimation results of the SURE method, obtained by using LIMDEP software (Green, 2007), are reported in Table 3. For a comparison, the results derived from the three models considered separately (SM) are also presented.

Estimation points have the sign expected for all these models: the $SFC_{20°C}$ decreases as the number of accumulated trucks (N_t) increases; whereas the MPD and IRI increase as the number of trucks increases. These findings are consistent with other relationships of pavement deterioration process contained in the literature. The t-statistic indicates that parameters α_1, α_2, and α_3, associated respectively to $SFC_{20°C}$, MPD, and IRI are statistically different from zero at 90% confidence level in all three models.

Table 3. Estimation results for the SURE model (applied to the SFC20°C, MPD and IRI) and corresponding Separate Models (SM)

Variables	Parameters	SURE			SM			
		Estimation Point	Standard error	t-statistic		Estimation Point	Standard error	t-statistic
$SFC_{20°C}$	α_1	-0.00039	0.00001335	-29.35		-0.00039	0.0001332	-29.44
					Log-likelihood	-173.673		
MPD	α_2	0.04686	0.00233	20.09		0.04693	0.00235	19.98
					Log-likelihood	48.019		
IRI	α_3	0.00133	0.00018	7.27		0.00133	0.00018	7.23
					Log-likelihood	-88.334		
Log-likelihood		-211.328				-213.988		
Numb. of observations		72				72		

(for each performance indicator)	
−2(LLR−LLU)	5.32
p-value	0.15

The likelihood ratio statistic is −2(LLR−LLU), where LLR and LLU are the log-likelihood values at convergence for uncorrelated and correlated conditions, respectively (Greene 2003). In addition, −2(LLR−LLU) has the chi-square distribution with k degrees of freedom, where $k=M(M-1)/2$. It is shown in Table 3, that LLR=-173.67+48.02-88.33=-213.99, LLU =-211.33, and −2(LLR−LLU)=5.32. In this particular case with $k=3$, this corresponds to a p-value 0.150 and the null hypothesis cannot be rejected at any significance level less than this value.

5.2 Forecasting Accuracy

The system of equations of the pavement deterioration model for estimating the values of the SFC$_{20°C}$, MPD and IRI over time as a function of the cumulative number of trucks (N_t) is as follows:

$$SFC_{20°C} = SFC_{20°C,base} \cdot (e^{\alpha_1 N_t})$$
$$MPD = MPD_{base} + \alpha_2 \cdot log(N_t) \qquad (7)$$
$$IRI = IRI_{base} + \alpha_3 \cdot N_t$$

where $\alpha_1 = $ - 0.00039, $\alpha_2 = $ 0.04686, and $\alpha_3 = $0.00133 in the case study; with the SFC$_{20°C}$ expressed numerically but positive values smaller than 100; the MPD in mm; the IRI in mm/m; the accumulated number of trucks expressed in $N_t/10^4$; and the logarithm is in base e (the system model is valid for $N_t \geq 10^4$).

As an example, using as a possible reference for a comparison the arithmetic mean μ ($\mu = \frac{\sum_{i=1}^{N} x_i}{N}$ of the sample of measurements $x_1,\ldots, x_{n,}$) one estimates after a cumulative number of trucks (N_t) equal to $2.8 \cdot 10^6$ (computed at year 2010 respect to year 2007) and $5.31 \cdot 10^6$ (computed at year 2012 respect to year 2007) values of SFC$_{20°C}$ respectively of 49.61 and 44.98 against corresponding average values of 54.51 and 43.72 measured in the field; MPD equal to 1.64 and 1.68 mm against means of 1.62 and 1.64 mm based on measurements in the field; and finally IRI equal to 2.59 and 2.92 m/km (mm/m) against means of 2.41 and 2.67 m/km (mm/m) observed in the field. This comparison shows an acceptable level of conformity between the predicted and observed values of aforementioned pavement performance indicators.

6. Summary and Conclusions

This research was motivated more especially by the need to individualize a methodological approach that appears to be more appropriate for showing the possible interrelation among different performance indicators while accounting for the full performance of a pavement over time. In particular, the seemingly unrelated regression equations (SURE) method is investigated to capture the deterioration process of pavement indicators considered with correlated error terms.

To achieve the paper's goal, an Italian motorway connecting the cities of Salerno and Reggio Calabria was monitored. Three performance indicators of pavement known as the side force coefficient (SFC$_{20°C}$), the international roughness index (IRI), and the mean profile depth (MPD) were more especially measured in three different time periods on a same section of this motorway.

After an exploratory analysis, a system based on the seemingly unrelated regression estimation (SURE) technique, which accounts for the correlation among the error terms in each seemingly unrelated equation in order to improve the parameter estimates, was developed. Regression parameters were estimated by the Maximum Likelihood Method.

It was found that estimation points have the signs expected: the SFC$_{20°C}$ decreases as the number of accumulated trucks increases; whereas the MPD and IRI increase as the number of trucks increases. These findings are consistent with other relationships of pavement deterioration process contained in the literature. The t-statistic indicates that regression coefficients associated respectively to SFC$_{20°C}$, MPD, and IRI are all statistically significant at 90% confidence level.

The log-likelihood of the SURE model is found to be a bit greater than that of the three separate models (SM).

Moreover the p-value of 0.15 may lead that the null hypothesis cannot be rejected at any significance level less than this value. This supports that the aforementioned three performance indicators should be jointly considered in the performance of a pavement over time accounting for the correlation among error terms.

The model developed in this paper produces an acceptable level of conformity between the predicted and measured performance measures. Therefore, this can be useful for many application such as the estimation of pavement rehabilitation needs over time, quantifying the performance modifications of pavement due to a variation of traffic demand, individualising the treatment type of a pavement that appears to be more appropriate in relation to a different deterioration process of one or more performance indicators.

Although this paper represents an interesting advancement in the assessment of performance measures of a pavement, more road sections should be investigated for a more consolidated verification of results obtained. However the method followed in the current paper, which is based on the use of the SURE model, represents a considerable potential in analysing jointly different performance indicators. Therefore, research needs to be addressed towards applying this statistical approach for making further developments possible.

Acknowledgments

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