Global Journal of Information Technology: Emerging Technologies

Volume 7, Issue 3, (2017) 157-162

www.gjit.eu

Route 93, Arizona's IRI estimation using least squares method and fuzzy logic

Sebnem Sargin Karahancer, Department of Civil Engineering, Faculty of Engineering, Transportation Laboratory, Suleyman Demirel University, Isparta 32260, Turkey.
Ekinhan Eriskin, Department of Civil Engineering, Faculty of Engineering, Transportation Laboratory, Suleyman Demirel University, Isparta 32260, Turkey.
Buket Capali, Department of Civil Engineering, Faculty of Engineering, Transportation Laboratory, Suleyman Demirel University, Isparta 32260, Turkey.
Serdal Terzi*, Department of Civil Engineering, Faculty of Engineering, Transportation Laboratory, Suleyman Demirel University, Isparta 32260, Turkey.
Mehmet Saltan, Department of Civil Engineering, Faculty of Engineering, Transportation Laboratory, Suleyman Demirel University, Isparta 32260, Turkey.

Suggested Citation:
Karahancer, S. S., Eriskin, E., Capali, B., Terzi, S. & Saltan, M. (2017). Route 93, Arizona's IRI estimation using least squares method and fuzzy logic. *Global Journal of Information Technology: Emerging Technologies*. *7*(3), 157-162.

Received July 02, 2017; revised October 11, 2017; accepted November 29, 2017.
Selection and peer review under responsibility of Prof. Dr. Dogan Ibrahim, Near East University, North Cyprus.

Abstract

Serviceability was found to be influenced by longitudinal and transverse profiles as well as the extent of cracking and patching. The amount of weight to assign to each element in the determination of the overall serviceability is a matter of subjective opinion. International roughness index of highway pavements has been estimated by least squares and fuzzy logic methods and compared. For these models, Route 93, Arizona experimental data have been used. Annual freeze–thaw occurring days, depending on years, have been used for modelling. The developed model with least squares method has a high regression value. This approach can be easily and realistically performed to solve problems that do not have a formulation or function for the solution.

Keywords: International roughness index, least squares method, modelling, estimation, fuzzy logic.

* ADDRESS FOR CORRESPONDENCE: **Serdal Terzi,** Department of Civil Engineering, Faculty of Engineering, Suleyman Demirel University, Isparta 32260, Turkey. *E-mail address*: serdalterzi@gmail.com

1. Introduction

Highways are one of most important structures for the development of a civilization. Bitumen is widely used as a binder in the construction of highways. Because bitumen is an expensive material, the construction of highways is costly. Therefore, it would be a wise step for road professionals to provide long-term service life of the highway. As long as the service life increases, the cost–benefit ratio also increases. More sustainable highways are produced in this way.

According to recent research, highways designed for 20 years' service life are only available for 11 years without any maintenance and rehabilitation (M&R) (Shahin, 2002). It is an optimisation problem to apportion the highway budget between M&R and new construction. To solve this problem, it is important to create an optimum pavement management system (PMS). PMS can be explained as creating M&R programmes to obtain the maximum benefit with a limited budget. Most suitable PMSs can be created according to the physical measurements and the structural road characteristics. Although instant measurements are the best way to get the correct results of the highway, the situation of the highway in the future is of great importance to create a suitable PMS.

There is a linear relationship between pavement performance and driving quality. In fact the relationship is accepted as one and is called service ability. The service ability of the pavement varies, depending on the traffic and climate (Haas, 2001). According to the AASHTO Road Test, 95% of the service ability could be obtained with the longitudinally roughness measurements (Carey & Iric, 1960). Measured longitudinally roughness data demonstrate driving comfort. So, the World Bank developed the international roughness index (IRI) in 1982 (Sayers, 1986). IRI is a general index about the pavement condition, which is obtained with an 80 kph driving car measuring the longitudinally profile of the highway. The range of IRI is between 0 and 2.13, where 2.13 means not passable highway (Herguner, 2009). IRI could be used directly to determine the M&R programmes.

In this paper, IRI values are tried for modelling. Sarioglu (2013) model IRI for California depending on the annual freeze–thaw occurring days and years with 80% correlation. For the modelling process, annual freeze–thaw occurring day's data from long-term pavement performance (LTPP) programme are used (Federal Highway Administration, 2013). Least squares method and fuzzy logic is used for modelling IRI.

2. Estimation of IRI

2.1. Trend Analysis

Estimations are generally based on mathematical and statistical methods. One of the estimation methods is trend analysis. Trend analysis can be explained to express the dataset collected for a long time period in a linear or non-linear way (Yalcinoz, Herdem & Eminoglu, 2002). The accuracy of the results of trend analysis should be checked before use. The usability could be determined with a regression analysis.

The least squares method used in this paper is a standard approach in regression analysis. The mean of this method is minimising the sum of the squares of the errors, which are the difference between the collected and calculated data (Eq. (1))

$$e = \sum_{i=1}^{n} \left(x_i - f\left(y_i \right) \right)^2 \quad (1)$$

where n is the number of data, x_i is the collected result for *i*th data, x_i is the calculated result for *i*th data and e is the sum of the errors. As long as e goes to 0, the correlation goes to 1.

2.2. Fuzzy Logic

In recent years, the fuzzy set theory has found a large number of applications and it has become one of the methods for dealing with complexity, uncertainty and imprecision in various systems. The fuzzy set theory has found its place between other theories, such as probability theory, but also neural networks and interpolate systems (Hoogendoorn, Hoogendoorn-Lanser & Schuurman, 1999).

Fuzzy sets arise from an extension of the classical sets for representing concepts that exhibit a gradual transition from membership to non-membership. Mathematically, a set is a collection of elements that share a common property. Whether an element has a particular property, however, cannot always be determined in an exact way. There are a large number of concepts in which an element can have partial membership to a set.

The heart of a typical fuzzy system is formed by a knowledge base in which the approximate working of the fuzzy system is described as a collection of fuzzy if-then rules. An inference mechanism compares the inputs of the system against the knowledge stored in the knowledge base and determines the system's output using the given inputs and the available knowledge in the knowledge base. Usually, the input signals are crisp, i.e., the inputs to the system are specified in a precise manner. In many cases, the outputs are also crisp as a precise action is required from the fuzzy system.

The objective of such an estimation system is to achieve a more efficient use of the PMS and to reduce the testing time conducted for obtaining IRI.

The main motivation for using fuzzy logic for this specific problem is the complexity of the modelling task: a large number of parameters can be identified, while their influence is not precisely known. However, experts are available having some (vague) ideas concerning the dynamics of the system. Fuzzy logic is ideally suited for model development when the exact dynamics of the system are only partly known and understood, but some vague ideas and expert knowledge are available. To design a fuzzy system, the following general steps have been taken:

- Definition of system boundaries (expected IRI)
- Definition of relevant variables, both input and output (see Figure 17)
- Fuzzification of the variables
- Definition of relations between the defined variables (the rule bases, see Figure 18)
- Defuzzification of variables
- Calibration of the model
- Evaluation of the model

3. Results and Discussion

In this paper, for estimating IRI values a trend analysis has been made. A general form of an equation is determined in order to analyse the trend between years and annual freeze–thaw occurring days (Eq. (2))

$$f(x_1,x_2)=\begin{bmatrix} a+b*x_1+c*x_2+d*\left(\dfrac{x_1}{x_2}\right) \\ +e*\left(\dfrac{x_1}{x_2}\right)+f*x_1^2*x_2+g*x_2^2*x_1 \\ +h*x_1^2*x_2^2+i*x_1*x_2+j*\left(\dfrac{x_2}{x_1^2}\right) \\ +k*\left(\dfrac{x_2}{x_2^2}\right)+l*\left(\dfrac{x_2}{x_1^3}\right)+m*\left(\dfrac{x_2}{x_1^4}\right) \end{bmatrix} \quad (2)$$

where x_1 and x_2 are time and annual freeze–thaw occurred days, respectively, and $[a,b,c,\ldots,m]$ are constants. To solve the equation a program has been written. The algorithm is as follows:

Step 1. Read the input variables x_1,x_2 and output value x_1,x_2

Step 2. Input the limit values for $a,b,c,\ldots,m$

Step 3. Calculate the $f(x_1,x_2)$ for every x_1 and x_2 within limit values

Step 4. Calculate least squares with $f(x_1,x_2)$ and $f(x)$

Step 5. Give the input values which gives the minimum least squares

Eq. (3) can be obtained with the help of the above algorithm. The unnecessary constants obtain 0, so they do not exist in Eq. (3).

$$f(x_1,x_2)=\begin{bmatrix} 0,06168+0,0282158*x_1+0,00005158*x_2 \\ +10,812142*\left(\dfrac{x_1}{x_2}\right)+0,0337653*\left(\dfrac{x_2}{x_1}\right)+0,0079938*\left(\dfrac{x_2}{x_1^2}\right) \\ +0,2648001*\left(\dfrac{x_1}{x_1^2}\right)+0,00003235*\left(\dfrac{x_2}{x_1^3}\right)+0,0003177*\left(\dfrac{x_2}{x_1^4}\right) \end{bmatrix} \quad (3)$$

The IRI values from LTPP are compared with the IRI values calculated from Eq. (3). The comparison is seen in Figure 1.

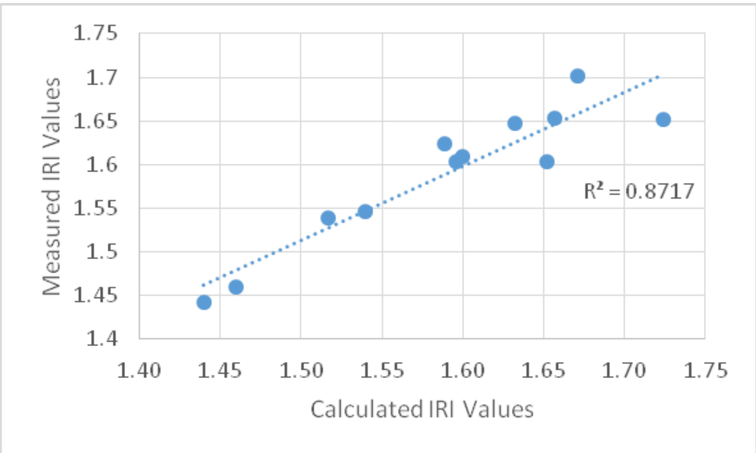

Figure 1. Correlation between the collected and calculated IRI values

As shown in Figure 1, the calculated IRI values in Eq. (3) are close to the IRI values obtained from the LTPP programme. The correlation between them is obtained as 87%, which is a high correlation value and could be used for estimating the IRI values for a future time.

On the other hand, the IRI values from LTPP are tried to model with a fuzzy logic. A model was built with two input parameters as years and annual freeze–thaw occurred days versus one output as IRI value. The structure, the surface and the rules of the model are seen in Figure 2. The developed IRI forecasting system was tested with data of LTTP in Arizona. After tuning the system's parameters using expert knowledge, a very good estimation performance was achieved (99% prediction quality). Figure 3 presents the prediction quality.

(a) (b) (C)

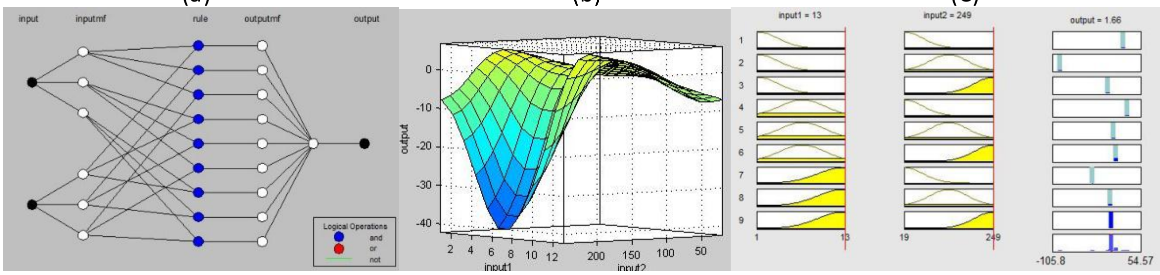

Figure 2. (a) Structure, (b) surface, and (c) rules of the model

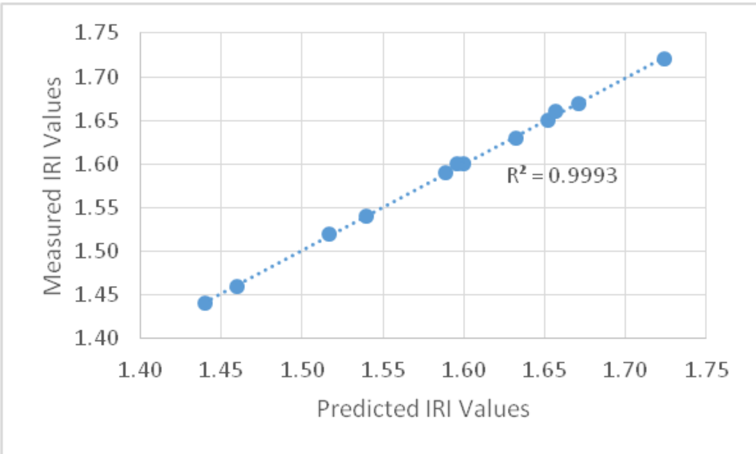

Figure 3. Correlation between the measured and predicted IRI values

As seen in Figure 3, the correlation is close to one, so the prediction is almost the same as the real value. According to the correlation seen in Figure 3, fuzzy logic could be used for estimating the IRI values. However, the model obtained from fuzzy logic can only estimate the values between the limit values used for training. So IRI prediction for a future time is not possible with the model. Therefore, a high correlation has almost no meaning for this study.

4. Conclusion

In this paper, data from Route 93, Arizona obtained from LTPP programme was tried for modelling. Least squares method and fuzzy logic were used for modelling the data. As a result, the following conclusions can be drawn:

- IRI can be modelled, depending on the annual freeze–thaw occurring days and years
- Least squares method can be used for modelling IRI
- Obtained model with least squares method has a high regression value, which shows the usability for this model
- The model obtained from fuzzy logic has a higher regression value than that obtained from the least squares method. However, the model obtained from fuzzy logic can only estimate the values between the limit values used for training. Therefore, usability of the model for estimating the IRI for future time is not possible

References

Carey, W. N., & Iric, P. E. (1960). *The pavement serviceability – performance concept*. US: Highway Research Board Bulletin.

Haas, R. (2001). Reinventing the (pavement management) wheel. In *5th Annual Conference on Managing Pavements.*

Herguner, A. T. (2009). *Pavement management system for the motorway network in Turkey* (Unpublished Doctoral Thesis). Natural and Applied Sciences, Istanbul Technical University, Istanbul.

Hoogendoorn, S., Hoogendoorn-Lanser, S., & Schuurman, H. (1999). Fuzzy perspectives in traffic engineering. In *Workshop on Intelligent Traffic Management Models.*

Sarioglu, O. (2013). Mathematical modelling of IRI data from LTPP test section. *Electr. J. Constr. Technol.*, *9*(2), 1–6.

Sayers, M. W. (1986). The international road roughness experiment: Establishing correlation and a calibration standard for measurements. Access Date: 01 March 2017. www.deepblue.lib.umich.edu

Shahin, M. Y. (2002). *Pavement management for airports, roads and parking lots*. London, UK: Kluwer Academic Publishers.

Yalcinoz, T., Herdem, S., & Eminoglu, U. (2002). Yapay sinir aglari ile Nigde bolgesinin elektrik yuk tahmini. *Nigde Universitesi, Mühendislik-Mimarlik Fakultesi, 1,* 1-5.