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An Explicit Formulation for Estimation of Structural Number (SN) of Flexible Pavements in 1993 AASHTO Design Guide using Response Surface Methodology (RSM)

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ABSTRACT

In the 1993 AASHTO flexible pavement design equation, the structural number (SN) cannot be calculated explicitly based on other input parameters. Therefore, in order to calculate the SN, it is necessary to approximate the relationship using the iterative approach or using the design chart. The use of design chart reduces the accuracy of calculations and, on the other hand, the iterative approach is not suitable for manual calculations. In this research, an explicit equation has been developed to calculate the SN in the 1993 AASHTO flexible pavement structural design guide based on response surface methodology (RSM). RSM is a collection of statistical and mathematical methods for building empirical models. Developed equation based on RMS makes it possible to calculate the SN of different flexible pavement layers accurately. The coefficient of determination of the equation proposed in this study for training and testing sets is 0.999 and error of this method for calculating the SN in most cases is less than 5%. In this study, sensitivity analysis was performed to determine the degree of importance of each independent parameter and parametric analysis was performed to determine the effect of each independent parameter on the SN. Sensitivity analysis shows that the $\log(W_{8.2})$ has the highest degree of importance and the Z_R parameter has the lowest one.

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1. Introduction

Highway pavement plays a significant role in national profit-making activities. About one-fifth of mean household expenditure is directly associated with transportation. Personal transportation mainly includes private cars, which account for more than 90% of the total vehicle miles traveled (VMT). In addition, on average, about 90% of cargo transport is done using road systems [1]. Pavements are engineering structures that are important to our daily lives, commerce and trade, and national defense and we use them as roads, runways, parking lots, and driveways. Like any other engineering structure, the pavement is expected to be well built and durable enough for its lifetime. They are expected to perform well by providing a smooth running surface for traffic in various environmental conditions. To ensure this the pavement must be designed correctly [2].

To design the pavement, one must determine the thickness of different layers to avoid problems or failures on the pavement due to traffic loads and environmental issues [3,4]. The factors that affect the thickness of the pavement could be classified into four different categories: load and traffic, environment, materials, and failure criteria [5].

The earliest technique for pavement design was according to the basic principles of soil mechanics so that no satisfactory application results were obtained before 1960. In early 1970s, the officials and researchers reviewed and developed new design methods to achieve cost-effective pavement design resistant to traffic conditions [6,7].

The road test of the American Association of State Highway and Transportation Officials (AASHO) is perhaps the biggest and most prosperous test of controlled civil engineering in history, which took place more than half a century ago [8]. The 1993 AASHTO design guide is based originally on information obtained from the AASHO road test. This design guide is still a favorable standard for designing flexible pavements and has been used by many transportation agencies around the world [9]. The design equation used for this guide has been the subject of several studies [10–12]. In order to structural design of pavement, it is necessary to solve the 1993 AASHTO design equation with the aim of determining the structural number (SN). However, due to the complex and non-linear relationships in the design equations, determining the SN is a technical challenge. In addition, no research has been found to provide an explicit equation for determining the SN.

So far, various statistical and machine learning methods have been used with the aim of building empirical relationships in civil engineering [6,13–25]. One of the powerful methods for establishing empirical relationships between a number of input parameters and a response parameter is the response surface methodology (RSM), which is usually used as a design of experiment method. This method is a set of statistical and applied mathematics methods which is used to develop empirical models consisting of polynomial terms and the interaction between them. This method has recently attracted the attention of researchers in pavement engineering [13,18–21]. The RSM is classified as a statistical learning method, which is a subset of machine learning methods. Machine learning methods are also considered as a subset of soft computing.

In this paper, an explicit equation is developed to determine the SN for flexible pavements based on response surface methodology (RSM). Using this equation, one can determine the SN with high precision to design flexible pavements.

In this paper, first the response surface methodology is described and then the method of building the optimal RSM model to calculate the SN of flexible pavements is introduced. Then, in order to examine the developed model in more depth, sensitivity analysis and parametric analysis have been performed. Finally, the conclusions and recommendations for further research are presented.

2. The 1993 AASHTO design guide

Many agencies around the world apply the 1993 AASHTO Guide to design flexible pavement [8,26,27]. This guide is on the basis of a road test under a supervision of the AASHO. This road test has been designed to find the association between the sum of load repetitions and the function of pavements with different materials and thicknesses. The AASHO road test was carried out on six diverse loops built along Interstate 80 near Ottawa, Illinois and loading started in 1958 and was over in 1960 [28].

The major indices of the AASHO road test included the thicknesses of hot-mix asphalt (HMA), base, subbase and, diverse axle configurations used in various test loops. The impressions and information found in the experiment are then incorporated in various segments of the design equation that links the amount of applied axle load to the necessary pavement thickness. The AASHO road test has achieved significant results in pavement engineering, including the association between load and distress, known as the 4th power law. Furthermore, AASHO road test introduced noteworthy indices like serviceability, equivalent single axle load (ESAL), and SN. AASHO pavement design guideline document was first issued in 1961 under *AASHO Interim Guide for the Design of Rigid and Flexible Pavements*. Given that the equations achieved in the AASHO test had been on the basis of limited data obtained from loading for two years and just under one climatic situation (Ottawa, Illinois), the design guide has been remarkably upgraded in1972 and1993 to fulfill various needs and climatic circumstances at the national level. The newest reform is the 1993 AASHTO flexible pavement structural design and has not been replaced ever since. Though significant measures have been taken in this path in the last 30 years to move from this empirical guide to a mechanistic-empirical pavement design guide (MEPDG), high cost and lack of a database that can be used for regional calibration of the design guide has become a problem for many agencies. Thus, the AASHTO 1993 design equation (equation 1) is yet applied as a trustworthy designing equipment for the structural design of pavements in several states in the United States and different countries in the world [8,26,29]. The main equation for designing flexible pavements is as follows:

$$\log(W_{8.2}) = Z_R S_o + 9.36\log(SN+1) - 0.20 + \frac{\log\left[\dfrac{\Delta PSI}{4.2-1.5}\right]}{0.4 + \dfrac{1094}{(SN+1)^{5.19}}} + 2.32\log\left(\frac{M_r}{0.07}\right) - 8.07 \tag{1}$$

Where:

$W_{8.2}$: The number of permittable equivalent single axle loads (8.2 ton) during the designing life.

Z_R: Standard normal distribution, defined according to the level of reliability in this design.

S_o: Overall standard deviation in this design.

ΔPSI: Permittable loss of serviceability at the end of the life of design.

M_r: Resilient modulus of subgrade soil (in kg/cm ^{2}).

Reliability (Z_R) is the probability that a designed pavement section will perform well under traffic and environmental conditions during the design period. Design reliability is considered to make sure the real ESALs in the life cycle of the design do not surpass the calculated ESALs [10,30].

Loss in Serviceability (ΔPSI) is the amount of serviceability loss over the life of the pavement section. The serviceability of the road is basically assessed by the driving condition of the users of roads. The serviceability index is scored from 5 to 1, in which 5 indicates the best and 1 indicates the worst quality of ride [4,30].

Resilient Modulus (M_r), which is a significant index based on the 1993 AASHTO design guidelines, reflects the engineering properties of the subgrade soil. Because of weather fluctuations throughout a year, the resilient modulus of subgrade soil will change significantly. Thus, the efficacious resilient modulus is the value of the representative modulus under diverse climatic circumstances, and is determined according to possible damage to the pavement caused by various soil modules of the subgrade in different seasons [30].

Structural Number (SN) is a number representing the overall structural requirements of the pavement section. The SN is considered as an indicator to assess the pavement stability to the applied load. The SN value of a pavement section depends on the type of materials, thicknesses, and drainage capacity used in the pavement layers. The weaker the subgrade soil, the higher the SN needed under the same climate and load conditions [26,30].

For pavement design using the 1993 AASHTO design method, in equation 1, the parameters Z_R, S_o, $W_{8.2}$, PSI, and M_r are known, while the parameter SN is unknown. When the structural number SN of the design for primary pavement structure is found, it is essential to choose a set of thicknesses so that the presented SN, which is the result of thicknesses and the layer coefficients as well as the drainage coefficients, is greater than the required SN [1,31].

It can be seen that to determine the parameter SN, equation 1 is not written explicitly. One can use an iterative method to solve equation 1 to determine SN, or get the SN value from the nomogram given in the AASHTO guide. Huang pointed out in his famous book *Pavement Analysis and Design* [31] that the nomogram is highly suitable for finding SN, as the SN solution is very troublesome and requires a trial & error process. However, using the design chart will reduce the precision and leads to tedious and time-consuming calculations. Therefore, an explicit and direct formula to determine SN is beneficial for designing purposes.

3. The response surface methodology (RSM)

The RSM includes a series of statistical and math-based methods that can be used to develop, improve and optimize processes. RSM uses specially designed experiments to develop alternative models in such a way that engineers are able to study the relation between inputs and outputs throughout designing space [32,33]. In the present study, a second-order RSM is used to unfold the non-linear association between parameters of pavement design and SN. The variables used in the 1993 AASHTO flexible pavement design equation cab mentioned as M_r, W_{18}, Z_R, S_o, ΔPSI, and SN. In addition, the SN of the layer is regarded as an output variable. In order to establish a suitable approximation between the dependent variable Y and the independent variables or predictors, the relation can be shown like this:

$$\mathrm{Y} = \mathrm{f}\left(\mathrm{Z_R}, \mathrm{S_0}, \Delta\mathrm{PSI}, \log(\mathrm{w_{8.2}}), \log(\mathrm{M_r})\right) + \varepsilon \tag{2}$$

The type of the real response function f is yet to be known and can be extremely complex, and ε is a key letter which indicates other resources of variability which are not included in f. As a result, ε includes the impact of measurement errors in responses, other sources of diversity during the process or in the system, and any other (probably unknown) variable. We regard ε as a statistical error, and in general, we suppose it includes a normal distribution with an average value of 0 and a variance of σ^2. If the average value of ε is 0, we have:

$$\begin{aligned} E(Y) \equiv \eta &= E[f(Z_R, S_0, \Delta PSI, \log(w_{8.2}), \log(M_r))] + \mathrm{E}(\varepsilon) \\ &= f(Z_R, S_0, \Delta PSI, \log(w_{8.2}), \log(M_r)) \end{aligned} \tag{3}$$

The variables used in equation 3 are generally mentioned as natural variables, as we show them in natural measurement units such as pounds per square inch (psi). According to various RSM models, converting natural variables to coded variables x_1, x_2, ..., x_k is much more convenient. These variables are basically determined as dimensionless, with an average value of 0 and a similar standard deviation. Based on coded variables, the real response function is shown as:

$$\eta = f\left(x_1, x_2, ..., x_k\right) \tag{4}$$

RSM abilities are directly associated with the type of response function. In general, low-order polynomials are suitable for several fairly small-scale regions of the independent variable space. First-order and second-order models are used in a lot of cases. In cases where we have 2 independent variables, the first-order model is presented based on the coded variables:

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \tag{5}$$

The first-order model in equation 5 is often mentioned as the main effects model, as it just consists of the major results of the two variables x_1 and x_2. When we see an interconnection between these variables, it can be simply added to the model as follows:

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 \tag{6}$$

The curve in the real response surface is generally so robust that the first-order model (even when containing the interconnection term) is insufficient. A second-order model is probably necessary under such conditions. Regarding the two variables, the second-order model is presented as follows:

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{12} x_1 x_2 \tag{7}$$

The second-order model is broadly applied in RSM for various reasons, which includes the following [32]:

1. The second-order model is highly flexible. It may include many different functional forms; thus, it usually works fine as an estimation of real response surface.
2. It is not difficult to approximate the parameters (the β 's) in the second-order model. The least squares method must be utilized for this goal.
3. One will find much substantial practical experience showing that second-order models work quite fine for solving the problems related to real response surface.

Generally, first-order and second-order models could be shown as equations (8) and (9), respectively:

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k \tag{8}$$

$$\eta = \beta_0 + \sum_{j=1}^{k} \beta_j x_j + \sum_{j=1}^{k} \beta_{jj} x_j^2 + \sum_{i=1} \sum_{j=2}^{k} \beta_{ij} x_i x_j \tag{9}$$

In this study, to build the RSM model, Design-Expert software version 13 was used. This software allows the adjustment, analysis, and comparison of various functions, including linear, interactive (2FI), and quadratic polynomials. In addition, the significance of the model was measured by Fisher's exact test, and the precision of model function was examined by regression coefficient of determination (R^2). In addition, the effect of the input variables on the SN was studied using analysis of variance (ANOVA).

4. Establishing dataset for model training

To develop the RSM model, Eq. 1 was solved by considering the acceptable range of the parameters used in Eq. 1 and, the value of $W_{8.2}$ was determined for each set of the input parameters. This operation was carried out 20,000 times with respect to different parameters, including Z_R, S_o, ΔPSI, M_r, and SN (right side of equation 1) and thus, a dataset made up of 20,000 records consisting of five input variables (Z_R, S_o, ΔPSI, M_r and $W_{8.2}$) and one output parameter (SN) were created.

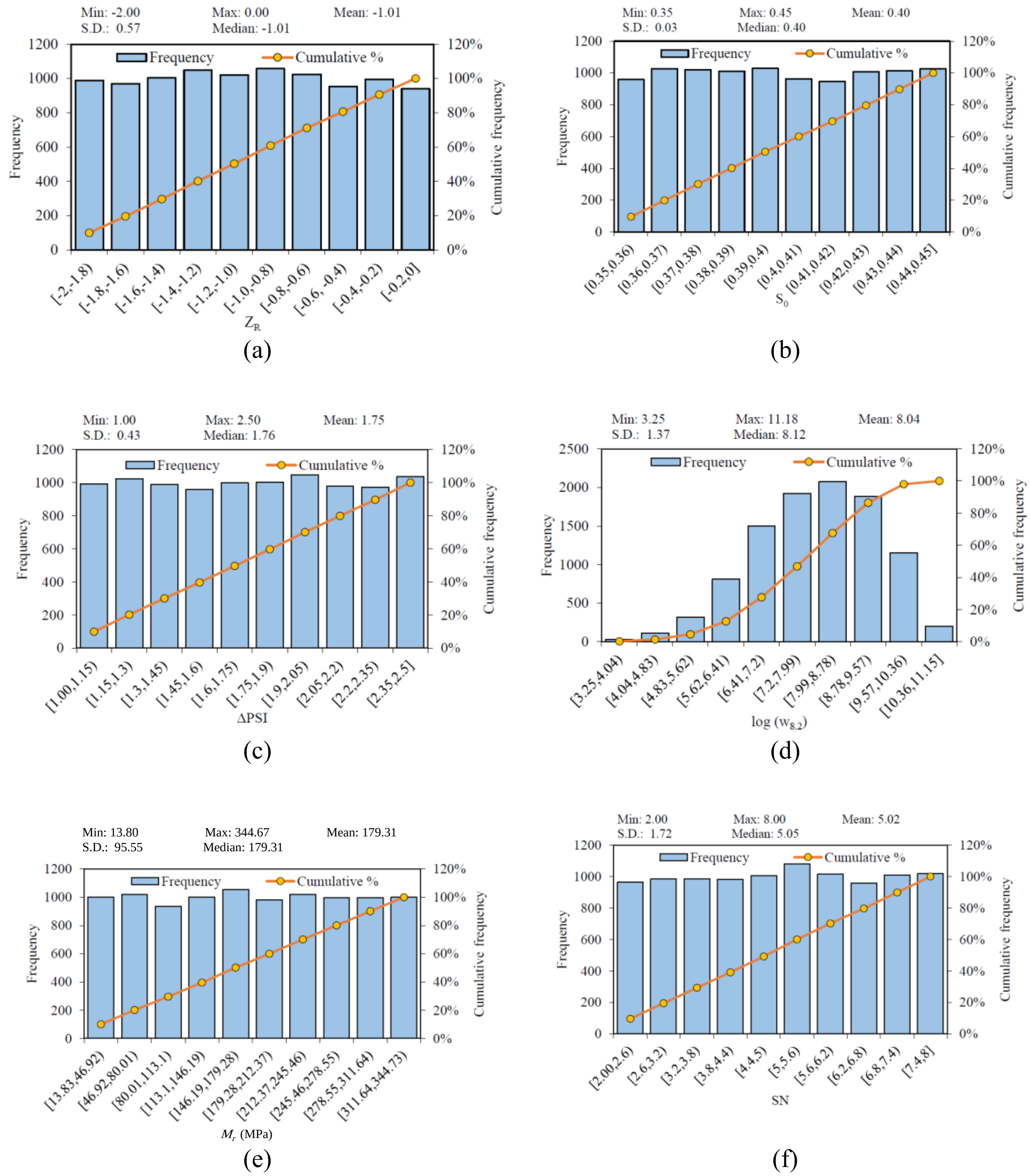

Fig. 1. Histogram and cumulative frequency plot for training set data for (a) Z_R, (b) S_o, (c) ΔPSI, (d) $\log(W_{8.2})$, (e) M_r, and (f) SN.

50% of the data points (10,000 records) were used for training and developing the model, and the other 50% (10,000 records) were used for testing and validating the model. The statistical characteristics of each input and output parameter, as well as the histogram and cumulative frequency plot of the training set data, are presented in Figure 1.

5. Modeling and evaluation

The RSM is a trial & error procedure. In the first place, a primary model containing every important factor is proposed according to the engineering experience. Then, the suitability of the model will be evaluated using residual plots, goodness-of-fit tests, and ANOVA. Subsequently, other models with more variables, fewer variables, or changed variables will be designed and compared with the original model. In this procedure, some variables may need to be transformed (e.g., logarithm). Finally, a model of RSM with the acceptable function will be selected for more analyses.

In this research, the second-order response function was used to establish a model based on the RSM for calculating the SN for flexible pavements. The modeling results based on this response function are presented in Table 1. In Table 2, in addition to the results of the second-order model, the results related to the first-order model are also provided. The coefficient of determination for the second-order model is 0.999, while this value is 0.960 for the first-order model, confirming that the relations between some input parameters and the output parameter are non-linear. The results of ANOVA for the second-order model are shown in Table 3. The table illustrates that just the overall standard deviation (S_o) term has been eliminated in the developed model. The reason for omitting this variable is that the existence of this parameter in the model has little effect on the accuracy of the model. It is also observed that the P-values are approximately equal to zero, excep for the term S_o^2, which indicates that the term S_o^2 is not as important as the other terms in the equation.

Table 1
Statistical metrics for the final second-order model.

Multiple R	Multiple R^2	SS Model	df Model	MS Model	SS Residual	df Residual	MS Residual
0.999	0.999	29616	19	1558	12	9980	0.001

R^2: Coefficient of determination
SS: Sum of square
df: degrees of freedom
MS: SS divide by the df

Table 2
Comparison of 1st order and 2nd order models for predicting SN.

model	df	F	P-value	R^2	Adj. R^2
2nd order Model	9980	1272521	0.000	0.999	0.999
1st order Model	14	53.61	0.000	0.960	0.942

df: degrees of freedom of residuals
F: F-Statistic
P-value: Probability value or Significant Level
Adj. R^2: Adjusted R^2

Table 3
Analysis of variance for the proposed model.

Model terms	SN Param.	SN standard error	SN t-statistics	SN p-value	-95.00% confident limit	+95.00% confident limit
Intercept	1.52245	0.026802	56.803	0.000000	1.46991	1.57499
Z_R	0.27167	0.010457	25.979	0.000000	0.25117	0.29217
Z_R^2	0.02945	0.001200	24.551	0.000000	0.02710	0.03180
S_o^2	-0.53748	0.120725	-4.452	0.000009	-0.77412	-0.30083
ΔPSI	-0.61230	0.014674	-41.727	0.000000	-0.64107	-0.58354
ΔPSI^2	0.35531	0.002105	168.779	0.000000	0.35118	0.35943
log ($w_{8.2}$)	0.94638	0.005364	176.447	0.000000	0.93587	0.95690
log ($w_{8.2}$) ^{2}	0.17009	0.000296	574.448	0.000000	0.16951	0.17067
log (Mr)	-2.14573	0.023067	-93.024	0.000000	-2.19094	-2.10051
log (Mr) ^{2}	0.89462	0.004082	219.156	0.000000	0.88662	0.90262
$Z_R \times S_o$	-1.74840	0.021547	-81.144	0.000000	-1.79063	-1.70616
$Z_R \times \Delta PSI$	0.14573	0.001468	99.270	0.000000	0.14285	0.14860
$S_o \times \Delta PSI$	-0.36025	0.028160	-12.793	0.000000	-0.41545	-0.30505
$Z_R \times$log ($w_{8.2}$)	-0.13652	0.000604	-226.026	0.000000	-0.13770	-0.13533
$S_o \times$log ($w_{8.2}$)	0.33252	0.010922	30.445	0.000000	0.31111	0.35393
ΔPSI×log ($w_{8.2}$)	-0.36868	0.000772	-477.709	0.000000	-0.37019	-0.36716
$Z_R \times$log (Mr)	0.31574	0.002454	128.661	0.000000	0.31093	0.32055
$S_o \times$log (Mr)	-0.80112	0.044918	-17.835	0.000000	-0.88916	-0.71307
ΔPSI×log (Mr)	0.84713	0.003107	272.655	0.000000	0.84104	0.85322
log ($w_{8.2}$) ×log (Mr)	-0.78185	0.001688	-463.209	0.000000	-0.78516	-0.77855

Equation 10 shows the final second-order RSM model developed in this research to calculate the SN for flexible pavement.

$$\begin{aligned} SN = {} & 1.52245 + 0.27167 Z_R + 0.02945 Z_R^2 - 0.53748 S_o^2 \\ & - 0.61230 \Delta PSI + 0.35531 \Delta PSI^2 + 0.94638 \log_{10}(w_{8.2}) \\ & + 0.17009 \log_{10}^2(w_{8.2}) - 2.14573 \log_{10}(M_r) + 0.89462 \log_{10}^2(M_r) \\ & - 1.74839 Z_R.S_o + 0.14573 Z_R.\Delta PSI - 0.36025 S_o.\Delta PSI \\ & - 0.13652 Z_R.\log_{10}(w_{8.2}) + 0.33252 S_o.\log_{10}(w_{8.2}) \\ & - 0.36868 \Delta PSI.\log_{10}(w_{8.2}) + 0.31574 Z_R.\log_{10}(Mr) \\ & - 0.80112 S_o.\log_{10}(Mr) + 0.84713 \Delta PSI.\log_{10}(Mr) \\ & - 0.78185 \log_{10}(Mr).\log_{10}(w_{8.2}) \end{aligned} \tag{10}$$

The performance of the model developed in association with the training and testing sets is illustrated in Figure 2. In this figure, different error-related performance metrics, including coefficient of determination (R^2), mean squared error (MSE), root mean square error (RMSE), and mean absolute percentage error (MAPE), are also given. These parameters can be calculated using Equations (11) to (14).

$$R^2 = \frac{\sum_{i=1}^{N}(T_i - \bar{O})^2}{\sum_{i=1}^{N}(O_i - \bar{O})^2} \tag{11}$$

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(O_i - T_i)^2 \tag{12}$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(O_i - T_i)^2} \tag{13}$$

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\frac{(O_i - T_i)}{T_i} \tag{14}$$

Where N denotes the number of observed data, T_i denotes the predicted values, O_i denotes the measured values, and $\bar{O}$ denotes the mean of the measured values.

It is evident that the proposed model can foretell the SN with an error percentage of less than 10%. For SN values greater than 4, the percentage of prediction error is even lower.

Residual frequency histogram for training and testing sets are illustrated in Figure 3. The normal distribution diagram fitted to the residual frequency histogram is also shown in this figure. The relatively good fit of the normal distribution diagram to the residual frequency data indicates that the proposed equation is reliable. It is also observed that in most cases, the residual frequency is less than 0.15. In practice, the value of the SN for a road with medium or heavy traffic is more than 3, and therefore in most of the cases, using the proposed equation contributes to the prediction of the SN of flexible pavements with an error percentage less than 5%.

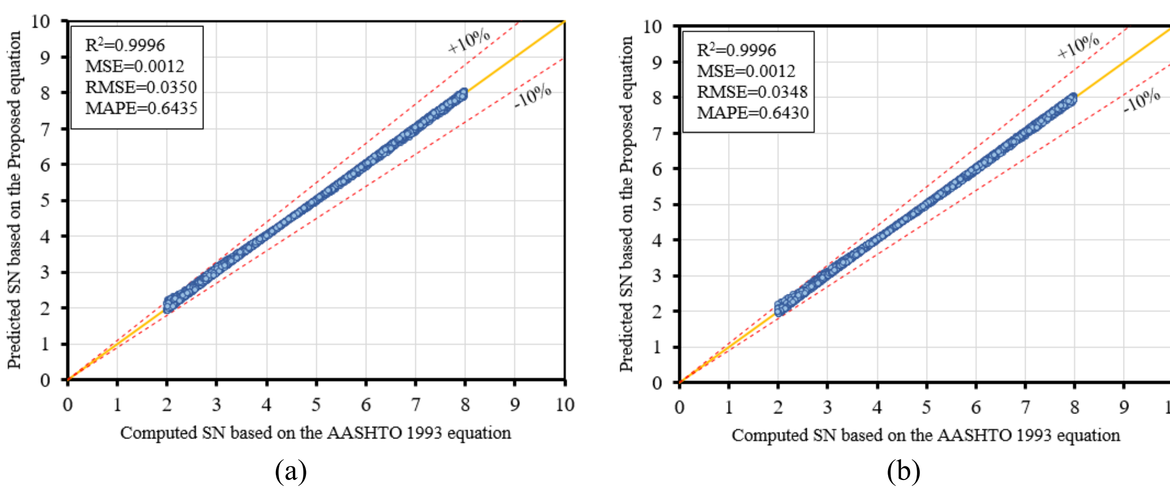

Fig. 2. Accuracy of the proposed equation for predicting SN based on (a) the training set, and (b) the testing set.

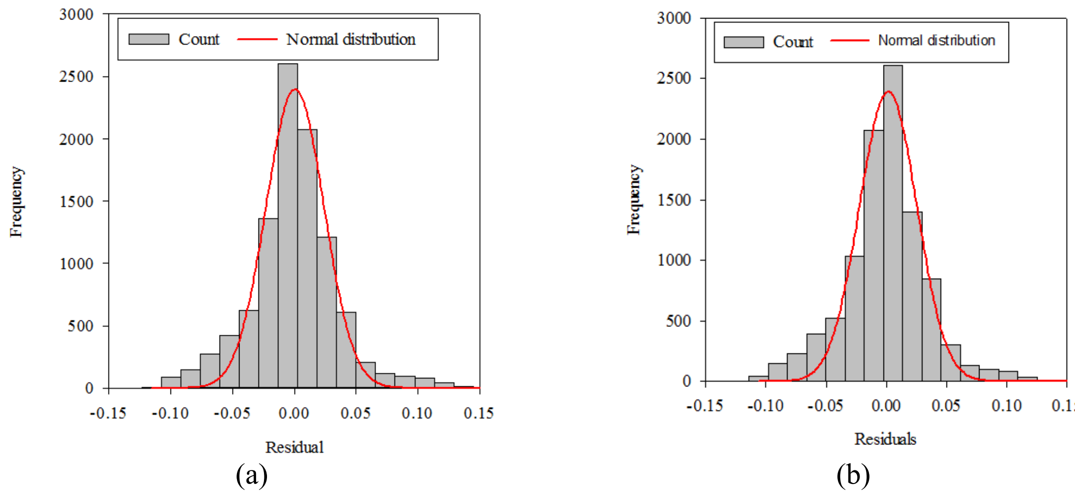

Fig. 3. Residual frequency histogram for (a) the training set, and (b) the testing set, and its comparison with normal distribution diagram.

6. Sensitivity analysis

In the present study, the cosine amplitude method (CAM) is applied for sensitivity analysis in the presented model. Based on all the methods below, this index of similarity makes use of a group of data samples, particularly *n* data samples. If these data samples are gathered, they can create a data array, *X* [6,34].

$$X = \{x_1, x_2, \ldots, x_n\} \tag{15}$$

every element x_i, in the data array *X* is a vector of length *m* itself, i.e.,

$$x_i = \{x_{i1}, x_{i2}, \ldots, x_{im}\} \tag{16}$$

Therefore, every data sample can be considered a point in an *m*-dimensional space, in which every point requires *m* coordinates to achieve a full representation. Every factor in a relation, r_{ij}, is the outcome of a pairwise comparing of two data samples, x_i and x_j, in which the power of the association between data sample x_i and data sample x_j is provided based on the following sensitivity index:

$$r_{ij} = \frac{\left|\sum_{k=1}^{m} x_{ik} \cdot x_{jk}\right|}{\sqrt{\left(\sum_{k=1}^{m} x_{ik}^2\right)\left(\sum_{k=1}^{m} x_{jk}^2\right)}}, \quad i, j = 1, 2, \ldots, n \tag{17}$$

Detailed assessment of Equation 17 demonstrates that the presented technique is associated with the scalar product for the cosine function. Once two vectors are collinear, their scalar product is unity; once the two vectors are at the correct angles to each other, their scalar product is 0 [34].

Figure 4 shows the sensitivity index values according to the figures achieved in the proposed equation and the sensitivity index values obtained using the 1993 AASHTO equation, and the significance of the input variables. According to this figure, the sensitivity index of all data inputs is greater than 0.8, which shows that each of these parameters has a significant impact on the SN. However, according to the CAM, the parameter log ($W_{8.2}$) is the most significant, while the parameter Z_R is the least significant parameter in predicting the SN. Furthermore, the sensitivity index values obtained from the proposed equation and the corresponding values obtained from the1993 AASHTO design equation are equal, indicating that the proposed equation has high accuracy in predicting the SN.

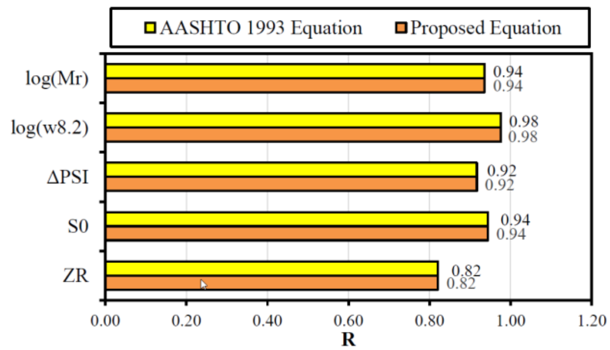

Fig. 4. Sensitivity index (r_{ij}) between SN and input parameters for the proposed equation and the 1993 AASHTO design equation.

7. Parametric analysis

In this study, we used parametric analysis to evaluate the influence of every pavement design input parameter ($W_{8.2}$, Z_R, S_0, M_r, ΔPSI) on the SN. To this end, the average value of each input parameter of the pavement design is considered, and the combined effect of changing the two input parameters on the SN is plotted by changing these two parameters within the ranges of minimum and maximum possible values. The assumed average value of each design input parameter is given in Table (4). Furthermore, the variation of SN caused by the simultaneous changes of the two input parameters is shown in Figure 5.

It can be seen that increasing S_0, decreasing Z_R (increasing reliability), increasing $W_{8.2}$, decreasing M_r, and decreasing ΔPSI increase the SN. Figure 5a shows that at low reliability values ($Z_R = 0$), increasing S_0 has little effect on increasing the SN. With increasing reliability (Z_R decreases), the influence of the parameter S_0 on the SN increases. It is also observed that the changes of the parameters S_0 and Z_R with SN are linear, while the changes of the parameters ΔPSI, $W_{8.2}$, and M_r with SN are non-linear. It is worth noting that the design period traffic of fewer than 1 million ESALs has a completely non-linear relationship with SN, and as the traffic increases beyond this amount, the relationship between SN and traffic changes linearly (Figures 5d, Figure 5e, and Figure 5f). The reason is that the development of the AASHTO pavement design model is based on traffic of less than 1 million ESALs. Therefore, it can be assumed that the SN is not actually sensitive to traffic if this equation is extrapolated to determine the SN.

Moreover, we observe that at low values of M_r, SN has a non-linear relationship with the variants of M_r, and if the value of Mr increases, the relationship between M_r and SN will be non-linear (Figures 5c and 5f). In fact, the AASHTO equation was developed for clay with low bearing capacity, and therefore, as the bearing capacity increases, it gradually becomes insensitive to changes in M_r.

Table 4
Assumed value of input parameters for parametric analysis.

model	$W_{8.2}$	Z_R	S_0	PSI	Mr
1st order Model	10^6	-0.841	0.45	2	34.5 MPa

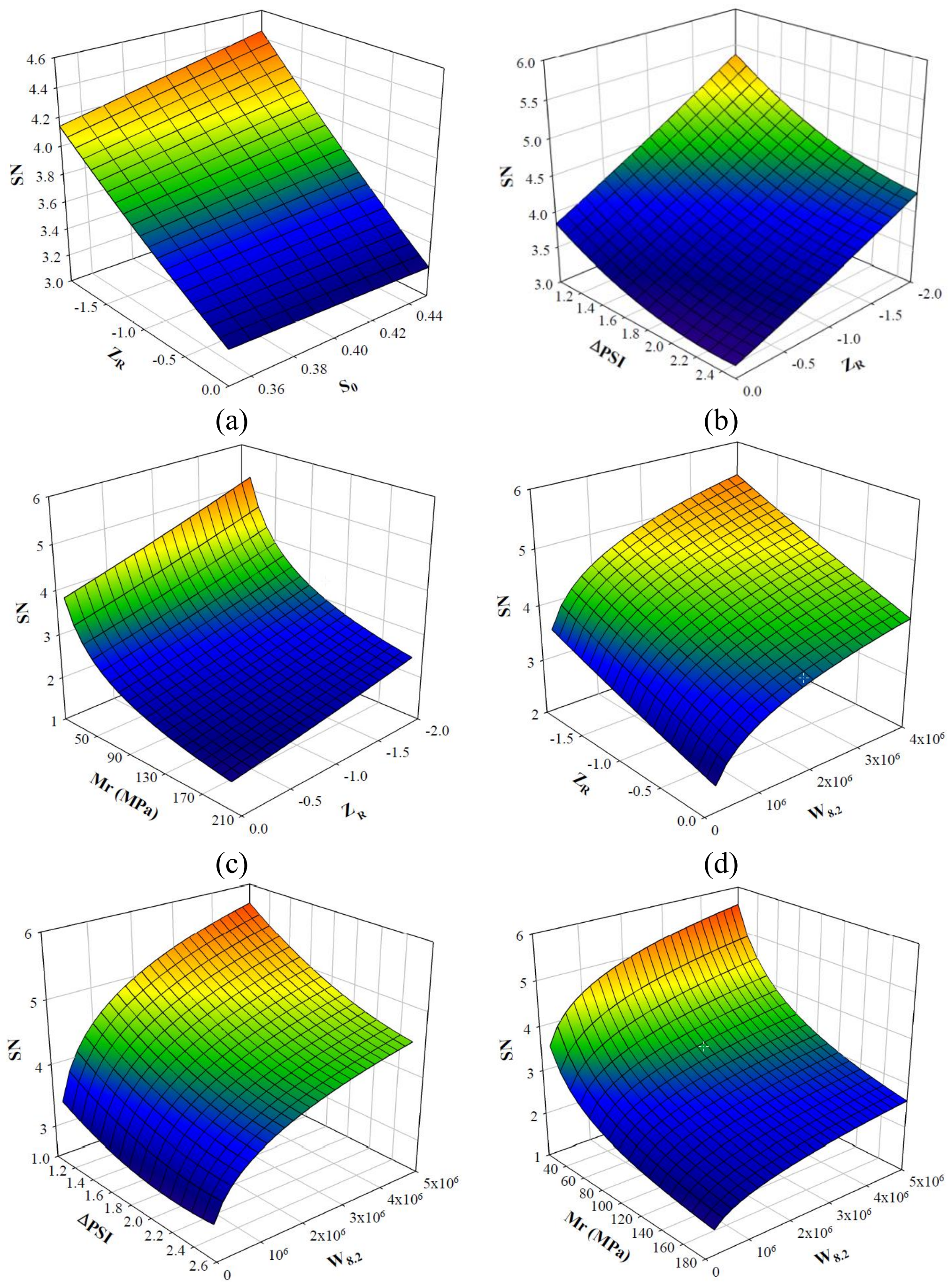

Fig. 5. Interactive effects of different input parameters on the SN.

8. Conclusion

This study was conducted to present an explicit equation for determining the SN for flexible pavement design using the RSM. Using the proposed equation, it is possible to accurately determine the SN with other inputs such as Z_R, S_o, $W_{8.2}$, ΔPSI, and M_r. The coefficient of determination of the equation proposed in this study for training and testing sets is 0.999. Furthermore, the residual frequency distribution shows that in the worst case, the proposed equation with an error of 5% allows a fast and precise SN prediction. Sensitivity analysis based on the CAM shows that the parameter $\log(W_{8.2})$ has the highest degree of importance and the Z_R parameter has the lowest one. Parametric analysis showed the non-linear relationship between the SN and the three parameters M_r, ΔPSI, $W_{8.2}$, and the linear relationship between the SN the two parameters S_0 and Z_R. The use of the proposed equation in this research eliminates the need for the iteration process to solve the 1993 AASHTO flexible pavements design equation and provides higher speed and accuracy than the 1993 AASHTO design chart. In the continuation of this research, the developed equation can be used for optimal design of flexible pavements. It is also suggested to use other machine learning methods to directly solve the 1993 AASHTO flexible pavement design equation.

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