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Investigating The Factors Affecting Pavement Overlay Service Life

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ملخص البحث

تعتبر دراسة العوامل المؤثرة على عمر الطريق مثل كثافة الامطار، سمك طبقات الرصف، درجة حرارة الهواء و احجام المرور هامة جدا لضمان اكتمال الفترة التصميمية للرصف كما خطط لذلك قبل التنفيذ.

هذة الورقة البحثية اعتمدت على برنامج (Neuro Solution 6) لبناء نموزج نستطيع من خلالة دراسة تأثير العوامل المختلفة على عمر الرصف الأسفلتى. فى هذا النموذج سيكون S(t) المتغيير التابع و العوامل المؤثرة ستكون المتغيرات المستقلة. المتغيرات المستقلة لكل قطاع اسفلتى سيتم استخراجها من مشروع (GPS-6) و الذى يعتبر احدى مشاريع (LTPP) و لكن المتغيير التابع S(t) سيتم حسابة بأستخدام (Third Degree Regression Model).

النتائج اظهرت ان (Neural Networks) عملى فى دراسة مدى تأثير العموامل المختلفة على عمر الرصف الأسفلتى.

البيانات المستخرجة من النموزج يمكن ان تساعد فى اتخاذ قرارات اوقات الصيانة و الترميم و ايضا معرفة التكالييف المحتملة و بالتالى وضع خطة مالية مناسبة.

Abstract:

No doubt, studying the effect of different factors as traffic loading, Atmospheric temperature, Density of rain fall or Precipitation, Pavement thickness, etc. on pavement service life is very important to guarantee the completion of pavements design period safely and as it was planned prior construction.

This paper relies on (Neuro Solution 6) program to build a network model through which studying the effect of various factors on pavement service life will be accomplished. In this model the pavement survival probability S(t) will act as dependent variable while factors affecting pavement service life as Traffic loading, Temperature, Precipitation, etc. will be the independent variables. Independent variables data for each pavement section will be extracted from General Pavement Studies (GPS-6) Experiment which is one of the Long Term Pavement performance (LTPP) projects while the dependent variable S(t) will be calculated using a third degree regression model.

The results show that the Neural Network model is applicable in estimating the effects of influential factors on pavement service life. The data extracted from the model can be used to assist in pavement rehabilitation decision-making, overlay design, and budget allocation.

Key Words: (LTPP) Long Term Pavement Performance, (GPS-6) General Pavement Studies.

INTRODUCTION

Pavement maintenance and rehabilitation is pivotal for infrastructure asset management. Preserving pavements in a suitable manner, extends their service life, and most importantly improves motorists' safety and satisfaction and saves public tax dollars (Anastasopoulos, P. C., & Haddock, J. E. 2009).

Studying the influence of different factors on pavement service life is not easy because it is so complicated to fully understand the real significance of each factor on pavement performance. No doubt, studying the effect of different factors as traffic loading, Atmospheric temperature, Density of rain fall or Precipitation, Pavement thickness, etc. on pavement service life is very important to guarantee the completion of pavements design period safely and as it was planned prior construction consequently saving billions of dollars spent by transportation agencies.

A Pavement management system requires prediction of pavement life. There are two terms to define pavement life, service life and remaining service life. Service life can be explained as the number of years after construction till the first rehabilitation. Each of service life and remaining service life of pavement can be used as tools for PMS. The purpose of remaining service life of a pavement is to assist pavement management system evaluating both the present and the future conditions of pavements, arrange projects according to the priority of one on the other, and improve the money spent on maintenance (Balla, C. K. 2016).

Different techniques have been proposed to study the effect of various factors affecting pavement service life. However, most of them are associated with various drawbacks either in historical data availability which is considered as a main part in using empirical methods or in causing damage to pavements as in destructive mechanical methods (Bourquin, J., Schmidli, H., Hoogevest, P. Van, & Leuenberger, H. 1998).

The main objective of this study is to develop a model through which it could be able to study the effect of the previously mentioned factors on pavement service life. This model is targeting to overcome the different drawbacks of both empirical and mechanical methods.

DATA COLLECTION AND DATA INPUT

A. Long Term Pavement Performance (LTTP)

Many queries stand as obstacles in front of pavement designers considering the selection of appropriate rehabilitation strategy to ensure the completion of pavement service life. In response to this need, The Long Term Pavement Performance (LTPP) program was developed trying to understand why pavements differ in their performance, consequently leading to better performing and more cost effective pavements (Gershenson, C. 2014).

One of the primary objectives of the Long Term Pavement Performance (LTPP) Studies was to "develop improved design methodologies and strategies for the rehabilitation of existing pavements." The study approach for rehabilitated asphalt concrete (AC) pavements involves construction of AC overlays over existing pavements to provide test sections with varying characteristics and observation of these test sections to advance industry's knowledge of how they perform and how this performance is affected by various parameters.

B. General Pavement Studies (GPS-6)

The GPS-6 experiment, "AC Overlay of AC Pavements," involved single test sections where an AC overlay is placed on an existing AC pavement. Table 1 presents only part of the data used in this study and extracted from GPS-6 experiment data base.

Table 1.

State	Section	Exp.	Original Pavement			Overlay Thick-ness (mm)	Age of Overlay (years)	International Roughness Index (m/km)
			Age Before Overlay	AC Thick-ness	Condition Before Overlay			
Alabama	11001	6B	12.7	84	Good	--	0.7	0.63
Alabama	14127	6B	14.7	211	Poor	43	4.8	0.88
Alabama	14129	6B	13.4	76	Good	38	4.7	1.07
Alabama	16012	6A	11.6	94	Good	33	11.6	2.42
Alabama	16019	6A	14.8	163	Poor	89	11.0	0.78
Alaska	21004	6B	13.8	91	Poor	46	0.2	1.7
Alaska	21008	6A	10.3	33	--	--	2.7	0.94
Alaska	26010	6A	13.2	53	Poor	43	7.5	1.08
Alaska	29035	6B	18.8	53	Good	97	1.2	1.01
Alberta	811804	6B	10.8	89	Poor	99	1.2	0.75
Arizona	46053	6A	20.5	81	Poor	120	4.6	1.39
Arizona	46054	6A	3.8	178	Good	53	5.8	0.99
Arizona	46055	6B	10.2	46	Poor	61	7.9	0.71
Arizona	46060	6A	21.5	99	Poor	102	3.5	0.67
British	826006	6A	17.5	81	Poor	53	16.4	1.3
British	826007	6A	2.7	64	Poor	132	11.3	0.73
California	66044	6B	33.3	81	Poor	122	13.7	0.91
California	68534	6B	22.5	119	Poor	89	1.7	0.78
California	68535	6B	23.8	188	Good	76	1.7	0.77
Colorado	86002	6A	--	147	Poor	71	--	3.01

With the aid of data in Table 1, Figure 1 can be drawn showing the relation between pavements overlay ages and the corresponding percentage of occurrence at different International Roughness Indices (IRI).

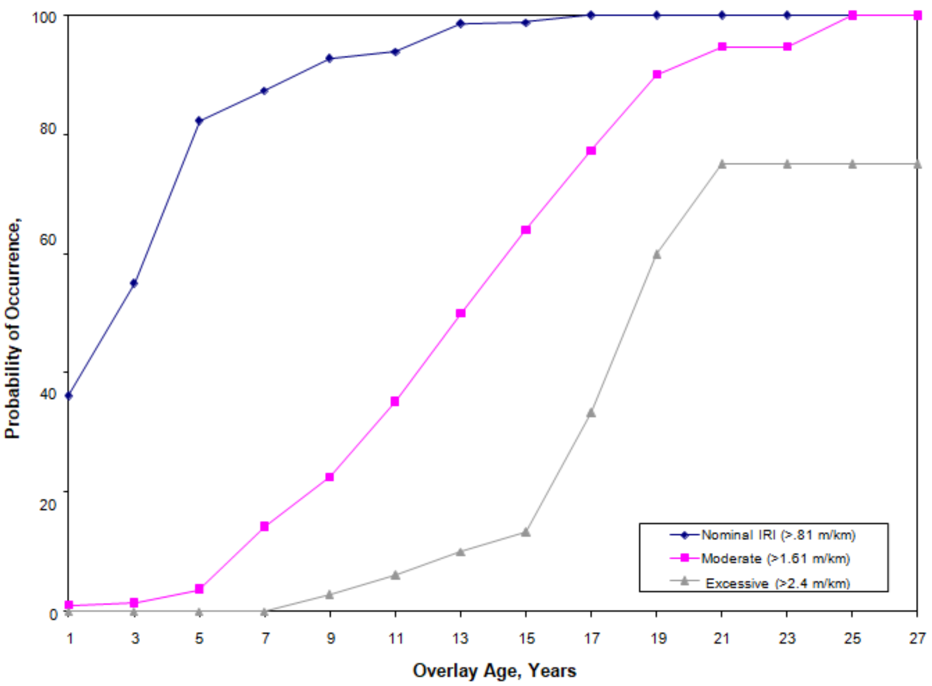


Figure 1. Frequency distribution for the GPS-6 test sections.

Since the main objective of this study is to investigate the effect of different factors as Equivalent Single Axle Load (ESAL), Temperature, Precipitation and etc. on pavement service life, it is necessary to extract the data concerning these factors from LTPP data base. Table 2 presents part of the data used in this study analysis.

Unfortunately, Data are not available for all pavement cross sections, Consequently, sections with incomplete data have been excluded from this study.

Table 2

Original Pavement			Overlay Thick-ness (mm)	Age of Overlay (years)	International Roughness Index (m/km)	Date of Overlay	Date of Overlay + Age of Overlay	Annual KESALs	Temperature (Celicius)	Precipitation (mm)
Age Before Overlay (years)	AC Thick-ness (mm)	Condition Before Overlay								
14.7	211	Poor	43	4.8	0.88	Apr-89	Jan. 1994		16.15	4.51
13.4	76	Good	38	4.7	1.07	Jun-89	Feb. 1994		16.71	3.92
11.6	94	Good	33	11.6	2.42	Jan. 1984	Jun. 1995	828	17.49	3.54
14.8	163	Poor	89	11	0.78	Apr. 1981	Apr. 1992		19.36	4.67
13.8	91	Poor	46	0.2	1.7	Jun-91	Aug. 1991	100	2.1	1.02
13.2	53	Poor	43	7.5	1.08	Dec. 1982	Jun. 1990	126	2.28	1.23
18.8	53	Good	97	1.2	1.01	Jul-90	Sep. 1991	39	1.07	2.27
10.8	89	Poor	99	1.2	0.75	Jun-93	Sep. 1994	136	2.68	1.37
20.5	81	Poor	120	4.6	1.39	1/10/1981	May. 1986	130	17.59	1.28
3.8	178	Good	53	5.8	0.99	1/5/1985	Feb. 1991	70	20.93	0.78
10.2	46	Poor	61	7.9	0.71	1/4/1985	Feb. 1993	400	22.36	0.62
21.5	99	Poor	102	3.5	0.67	1/10/1985	Apr. 1990	350	17.5	1.27

DATA ANALYSIS

This paper presents International Roughness Index (IRI) as a threshold limit to judge pavement performance. Road roughness is gaining increasing importance as an indicator of road condition (Ksaibati, K., & Mahmood, S. Al. 2002).

Pavement sections with (IRI > 2.4m/Km) will be considered to have reached its end of useable service life.

After the necessary data were obtained for pavement sections, a comprehensive statistical analysis was performed.

In this study, the data analysis have been done using (NEURO SOLUTION 6) program to accomplish an artificial neural network model through which we could study the effect of different factors as KESAL, Temperature, Precipitation, etc on pavement service life.

Kaplan-Meier survival analysis has been used to show the survival probability or behavior of pavement sections data along pavement overlay service life.

Regression analysis using (MATLAP) program has been used in achieving a third degree survival probability model to best describe Kaplan-Meier output data. Moreover, MATLAP has been used to draw various graphs illustrating different relations in this study.

A. Kaplan-Meier Analysis

The Kaplan-Meier method, which is called the product-limit method (Kaplan and Meier 1958) is a procedure often used to generate survival curves. In Kaplan- Meier method, the probability of survival to time (t), S(t), can be expressed as S(t) = p1*p2*…..*pt, where (pt) is the conditional probability of surviving t(th) year after having survived (t-1) years.

P(t) can be calculated as P(t) = (nt-dt)/nt=1-dt/nt, where (nt) is the number of pavements in good condition level at the start of the interval and therefore at the risk of failure during that short interval.

The number of pavements which ended their service during the time interval just after (t) is denoted as (dt). Then, (nt-dt) is the number of pavements surviving the interval.

The successive overall probabilities of survival S(1), S(2), …, S(t), are known as the Kaplan-Meier or product-limit estimates of survival.

The graph of S(t) versus the number of years, t, as shown in Figure 2 gives the Kaplan-Meier estimate of the survival curve and provides a useful summary of the data.

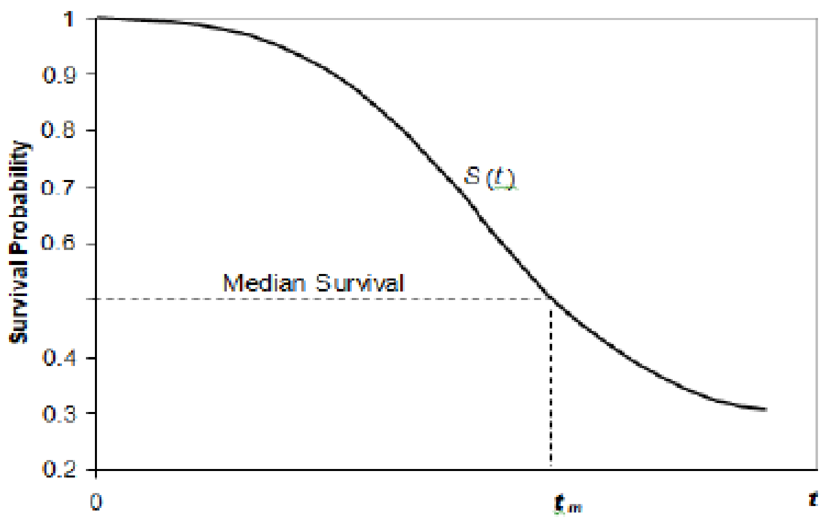


Figure 2 Survival curve

Using figure 1 graph with IRI > 2.4m/km as a threshold limit and total number of pavement sections = 99 to represent 100% probability of occurrence , we can calculate that at overlay age = 16, number of pavement sections exceeding 2.4m/km equals to 23 sections.

According to figure 1 graph, we can construct Table 3 and Table 4.

Table 3

Overlay Age	Cummulative number of X-sec reached IRI > 2.4m/km	No_of Pav. X-sec reached IRI > 2.4m/km for each individual year d(t)
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0
5	0	0
6	0	0
7	0	0
8	1.6 ≈ 2	2
9	3.2 ≈ 3	1
10	4.8 ≈ 5	2
11	6.4 ≈ 6	1
12	8 ≈ 8	2
13	9.6 ≈ 10	2
14	11.2 ≈ 11	1
15	12.8 ≈ 13	2
16	22.6 ≈ 23	10
17	32.6 ≈ 33	10
18	46.3 ≈ 46	13
19	59.10 ≈ 59	13
20	66.7 ≈ 67	8
21	73.5 ≈ 74	7
22	73.5 ≈ 74	0
23	73.5 ≈ 74	0
24	73.5 ≈ 74	0
25	73.5 ≈ 74	0
26	73.5 ≈ 74	0
27	73.5 ≈ 74	0

Table 4

Overlay Age	n(t)	d(t)	$P(t) = 1 - \frac{d(t)}{n(t)}$	S(t) = p(t)*p(t+1)*p(t+2)*.....
0	99	0	1	1
1	99	0	1	1
2	99	0	1	1
3	99	0	1	1
4	99	0	1	1
5	99	0	1	1
6	99	0	1	1
7	99	0	1	1
8	99	2	0.97	0.97
9	97	1	0.98	0.95
10	96	2	0.97	0.92
11	94	1	0.98	0.90
12	93	2	0.97	0.87
13	91	2	0.97	0.84
14	89	1	0.98	0.82
15	88	2	0.97	0.79
16	86	10	0.88	0.69
17	76	10	0.86	0.59
18	66	13	0.80	0.47
19	53	13	0.75	0.35
20	40	8	0.80	0.28
21	32	7	0.78	0.21
22	25	0	1	0.21
23	25	0	1	0.21
24	25	0	1	0.21
25	25	0	1	0.21
26	25	0	1	0.21
27	25	0	1	0.21

The main objective from studying Kaplan-Meier analysis method in our research is conducting the survival probability curve as shown in figure 2 to be used as an input data in studying the effect of influential factors on pavement service life using (NEURO SOLUTION 6) program.

Using the overlay age and survival probability S(t) columns in table 4, we can draw the survival curve to show how data behaves.

Actually, Drawing this relation will not produce a smooth curve as we have expected but broken lines as shown in figure 3 and this is because the data are not presenting a clear or an exact model or function. Consequently, we will rely on regression analysis method to best describe the Kaplan-Meier output data.

B. **Regression Analysis**

Regression analysis was achieved using MATLAP program so that the overlay age is the independent variable and the survival probability S(t) is the dependent one.

The model has achieved R^2= 0.9877, which is considered to be a precise presentation for the data. Figure 3 is a graph showing how far the survival probability regression model is best describing the original Kaplan-Meier output data. A third degree model was the best function to describe the Kaplan-Meier output data and is mathematically given as the following equation:

$$S(t) = -1.22*10^{-4}\,x^3 + 7.212*10^{-4}x^2 - 9.819*10^{-4}x^1 + 1.0002$$

A valid statistical approach must be used to evaluate the precision and accuracy of a condition prediction model. For regression models, the most commonly used parameter to evaluate the goodness-of-fit statistics is the R-square, which is the ratio of the sum of squares due to regression divided by the sum of squares about the mean. R-square has been used to judge the precision of the survival probability model or equation.

The model has achieved R^2= 0.9877, which is considered to be a precise presentation for the data. Figure 3 is a graph showing how far the survival probability regression model is best describing the original Kaplan-Meier output data.

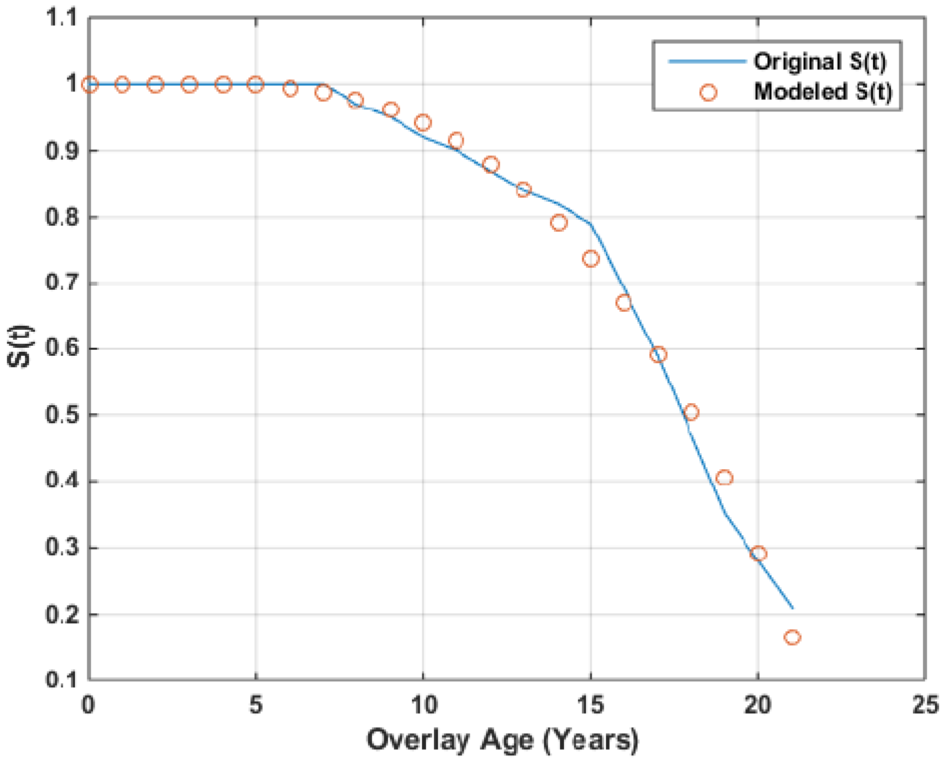


Figure 3 Kaplan Meier Output Versus Regression Model Output

C. Neural Network Model

Neural network deals with information in the same manner of our nervous system. The network learns by comparing its prediction for the records with the actual implemented ones and usually adjust the assumed weights given to data till reaching the optimum weights for the data under study (Sayers, M. W., Gillespie, T. D., & Paterson, W. D. (n.d). The main merit of neural networks is the ability to deal with data having the characteristics of either linear or non-linear relationship (Yu, J. 2005). In (NEURO SOLUTION 6) program The Data Manager module can deal with all Microsoft office programs. Table 5 shows part of the data used in building the neural network and have been implemented in NEURO SOLUTION 6 program.

Table 5

X1	X2	X3	X4	X5	X6	x7	X8	S(t)
11.6	94	33	11.6	2.42	828	17.49	3.54	0.895425
13.8	91	46	0.2	1.7	100	2.1	1.02	1.000031
13.2	53	43	7.5	1.08	126	2.28	1.23	0.981935
18.8	53	97	1.2	1.01	39	1.07	2.27	0.999849
10.8	89	99	1.2	0.75	136	2.68	1.37	0.999849
20.5	81	120	4.6	1.39	130	17.59	1.28	0.999069
3.8	178	53	5.8	0.99	70	20.93	0.78	0.994962
10.2	46	61	7.9	0.71	400	22.36	0.62	0.977302

Using (NEURO SOLUTION 6) program, Data implementation has been classified in the program as Input and Desired data. In this study the input data or input layers are as following:

X1 : Age before overlay, X2 : AC thickness, X3 : Overlay thickness, X4 : Age of overlay, X5: IRI, X6 : KESAL, X7 : Temperature in (celicius) and X8 : Precipetation in (mm).

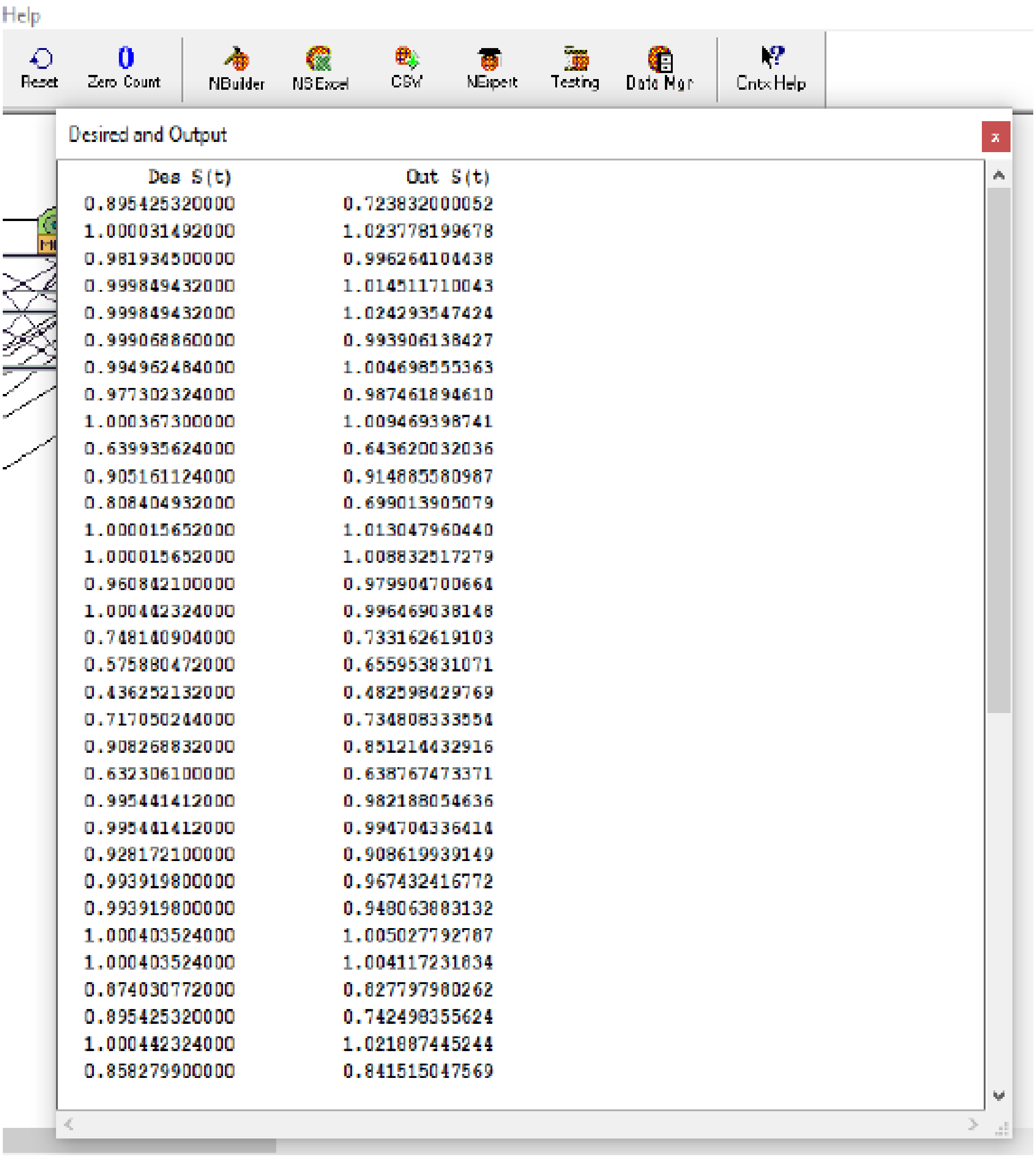
Pavement survival probability S(t) is the desired data or output layer in constructing neural network model and have been calculated for each pavement section using the survival probability regression model.

Not all the data have been used in constructing the neural network model, But part of these data have been used in building the network and are called training data, The rest of data have been used in neural network model validation and you will be responsible for specifying the percentage of both training and validation data.

Going through obvious steps through (NEURO SOLUTION 6) program the network model could be built by a simple click on (Build) icon then letting the program to start data analysis and finally you will be able to save your network model.

Using (Testing) icon you will be able to extract either training or testing data showing the variation between [desired S(t)] data implemented to construct the model and the [output S(t)] data calculated by the network model.

Figure 4 shows the training data while Figure 5 shows validation or testing data.



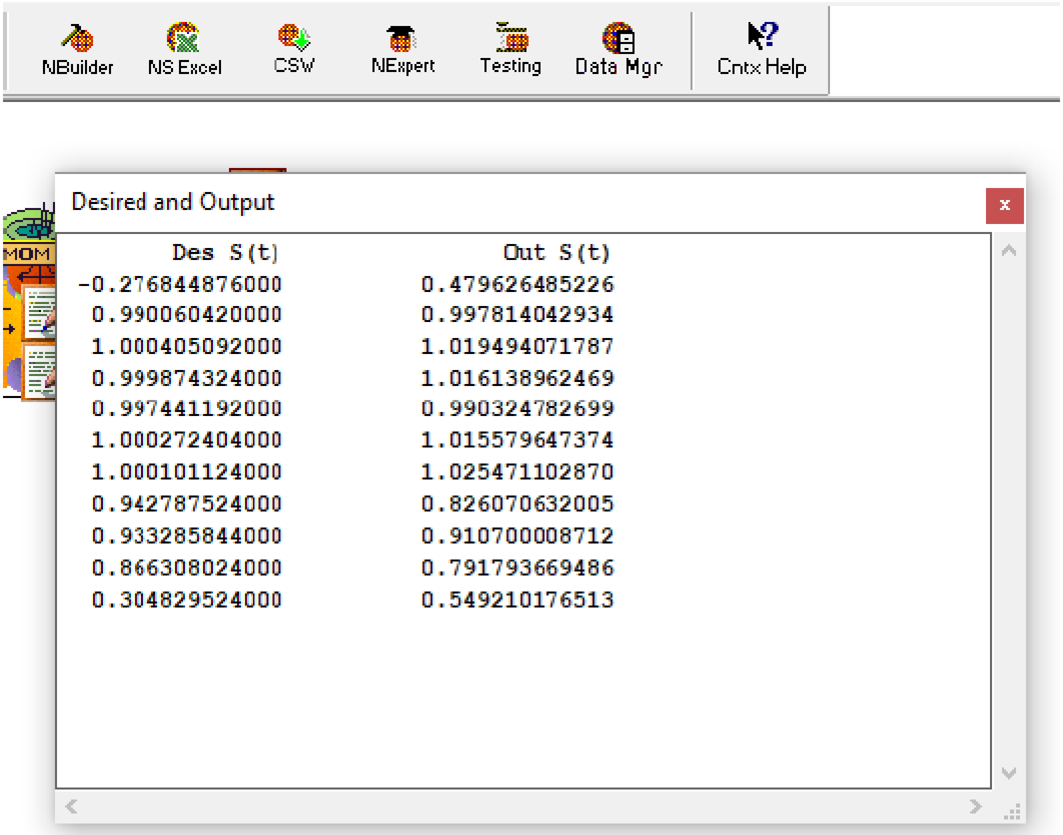
Help

Reset | Zero Count | NBuilder | NSExcel | CSV | NExpert | Testing | Data Mgr | Cntx Help

Desired and Output

Des S(t)	Out S(t)
0.895425320000	0.723832000052
1.000031492000	1.023778199678
0.981934500000	0.996264104438
0.999849432000	1.014511710043
0.999849432000	1.024293547424
0.999068860000	0.993906138427
0.994962484000	1.004698555363
0.977302324000	0.987461894610
1.000367300000	1.009469398741
0.639935624000	0.643620032036
0.905161124000	0.914885580987
0.808404932000	0.699013905079
1.000015652000	1.013047960440
1.000015652000	1.008832517279
0.960842100000	0.979904700664
1.000442324000	0.996469038148
0.748140904000	0.733162619103
0.575880472000	0.655953831071
0.436252132000	0.482598429769
0.717050244000	0.734808333554
0.908268832000	0.851214432916
0.632306100000	0.638767473371
0.995441412000	0.982188054636
0.995441412000	0.994704336414
0.928172100000	0.908619939149
0.993919800000	0.967432416772
0.993919800000	0.948063883132
1.000403524000	1.005027792787
1.000403524000	1.004117231834
0.874030772000	0.827797980262
0.895425320000	0.742498355624
1.000442324000	1.021887445244
0.858279900000	0.841515047569

Figure 4 Training Data



Des S(t)	Out S(t)
-0.276844876000	0.479626485226
0.990060420000	0.997814042934
1.000405092000	1.019494071787
0.999874324000	1.016138962469
0.997441192000	0.990324782699
1.000272404000	1.015579647374
1.000101124000	1.025471102870
0.942787524000	0.826070632005
0.933285844000	0.910700008712
0.866308024000	0.791793669486
0.304829524000	0.549210176513

Figure 5 Testing Data

Using data in Figure 4 and 5 it was able to draw Figure 6 showing how far the neural network model was precise in presenting data. Moreover, validation or testing data have achieved R-square equals to 0.9478 which is considered to be a precise presentation of the network model.

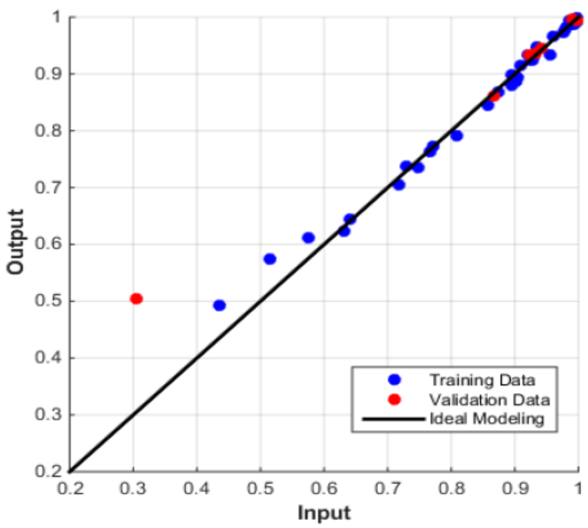


Figure 6. Input S(t) versus Output S(t) for both Training and Validation Data.

Results And Discussion

Production tool in (NEURO SOLUTION 6) Program is responsible for the usage of the network model, In other words, through production tool you will be able to insert your file including variables from (X1 to X8) and finally receives the output S(t) calculated from the network model, Consequently, being able to draw graphs showing how pavement perform through its service life.

To investigate the trend of the S(t) changes corresponding to a variable change, S(t) is computed using the network model at each desired variable value with other variables being the average.

Average values for variables or influential factors have been calculated using data in Table 5 to be as following:

X1 = 14.5 years, X2 = 117 mm, X3 = 78 mm, X4 = 7.9 years, X5 = 1.23 m/km, X6 = 256 KESAL, X7= 12.04 celicius, X8 = 2.09 mm.

Figure 7 shows the pavement performance or the survival probability for not only average but also high and low pavement sections. High pavement section represents the section with factors or variables that are proposed to increase the pavement service life, Conversely, Factors that are suggested to decrease the survival probability for pavement service life are related to the low pavement section.

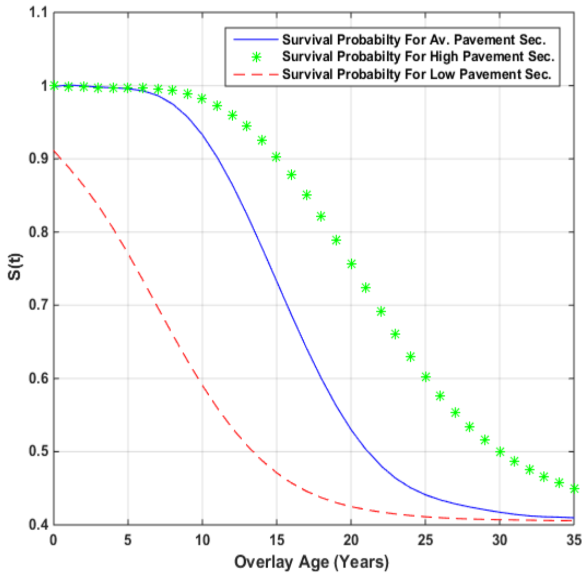


Figure 7. Overlay Age versus survival probability for different pavement sections

CONCLUSION

Various graphs could be drawn using the network model, For example by varying the temperature values and putting the other factors as average values, you will be able to construct a relation between the output modeled S(t) values and temperature values. Consequently, Evaluating the effect of temperature on pavement survival probability and be able to know how pavement perform under different ranges of temperature values.

The network model is not only able to investigate the effect of the influential factors on pavement overlay service life but also could be used to predict the behavior of newly and already overlaid pavement sections through their service lives, This is achieved by varying the overlay age values and implement the characteristics of either the newly or the already overlaid pavement section to get the corresponding S(t) values.

Knowing the behavior or the performance of the pavements from the beginning is considered a great advantage for all transportation agencies as this will assist not only in preserving huge investments in the pavements but also decreasing the money needed for rehabilitation.

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