Intelligent pavement rutting prediction models: the case of Norwegian main road network

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ABSTRACT : Prediction of pavement performance is a key process in the efficient management of pavement assets for a highway agency. There are a lot of tools that can be used to develop pavement performance prediction models, but the newest generation of tools belongs to the field of Artificial Intelligence. Rutting prediction models for stone mastic asphalt pavements are developed using multiple linear regression (MLR) and Artificial Neural Network (ANN) techniques, using data from the Norwegian national road databank (NVDB). Comparative study of the results is also conducted. The main conclusion from this study is that pavement rutting prediction models using the intelligent ANN technique predict pavement condition with a better accuracy than the classical MLR models.

KEY WORDS: Pavement performance prediction models, pavement rutting, Artificial Neural Network modeling, pavement condition measurement data, mastic asphalt concrete pavement.

1. INTRODUCTION

Pavements deteriorate with time under the combined effects of traffic and environment. To keep the condition of pavements at an acceptable level throughout their life span, the future performance of pavements should be predicted as accurate as possible. Permanent deformation in the form of rutting is one of the most important distress (failure) mechanisms in asphalt pavements. With increase in truck tire pressure in recent years, rutting has become the dominant mode of flexible pavement failure (Garba, 2002). Until a comprehensive purely mechanistic model is developed, which in spite of a great deal of researches, seems unlikely in the foreseeable future, the use of empirical or mechanistic – empirical models is very pragmatic (Yang, 2004).The best source of data for development of performance prediction models would be historical in-service road condition data. This paper presents development of rutting prediction models using data from the Norwegian Public Roads Administration's (NPRA) Nasjonal vegdatabank (NVDB). Comparative study of the predicting capability of intelligent artificial neural network (ANN) modeling technique versus the classical multiple linear regression (MLR) method is also conducted.

2. RUTTING AND POSSIBLE INFLUENCING FACTORS

Pavement deterioration greatly depends on traffic, pavement type, environmental and structural capacity factors. The selected variables based on the data available in the NVDB are summarized in Figure 1, and described in the sub-sections below.

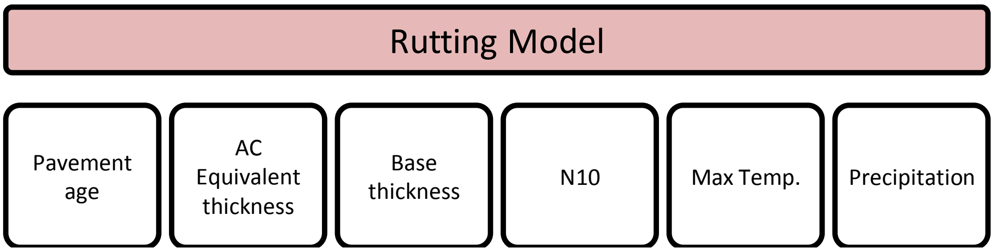

Figure 1: Adopted variables for the rutting model

2.1. Rutting

Rutting is the transverse depression of pavements along the wheel paths of traffic, Figure 2. In cold climates it is caused by two factors, permanent deformation and studded tire wears. Studded tire wear contributes significantly to rutting and is, on heavily trafficked roads, the most important cause of rehabilitation work (Bertelsen, Uthus, et al., 2005). In the NVDB, there is no differentiation between permanent deformation and wear, it is the total rut depth as observed on the pavements that is measured and registered. Hence, in order to model rutting progression from permanent deformation, a differentiation between the two is necessary.

Figure 2: Wheel path rutting (SINTEF web page), rutted pavement cut to show the deformations, and typical studded tire wear (Haugødegård, 2008).

Contribution from studded tires

A number of factors affect the amount of pavement wear from the use of studded winter tires. To determine the amount of pavement material which is worn by one passage of a vehicle, a term called SPS (specific wear) is defined in Norway and Scandinavia (Bertelsen, Uthus and Mork, 2005). It is the wear resistance of the asphalt surface course, and is defined as the average wear in grams worn from the surfacing when a passenger car equipped with 4 studded tires drives a 1 km distance. It is often more appropriate to specify the amount of worn material as volume instead of weight. This volume-based wear is referred to as the SPSV value. Typical SPSV values for some pavement types are provided in Table 1.

Table 1: Typical SPSV values for different pavement types (Ellingsen, 2008)

Pavement type	SPSV value
Stone Mastic Asphalt (SMA) – in Norwegian, Skjelletasfalt (Ska)	2 – 4
Asphalt Concrete – in Norwegian Asfaltbetong (Ab)	6 – 8
Asphalt Concrete – in Norwegian Asfaltgrusbetong (Agb)	6 – 12

Heavy vehicles and/or wheels with chains must be converted to a standard studded tire vehicle. It is therefore necessary to operate with an effective AADT, $AADT_{eff}$, to calculate the SPS or SPSV value. The SPSV value is computed using the following relation (Bertelsen, Uthus and Mork, 2005):

$$SPSV = \frac{\Delta A \cdot 10^5 cm/km}{AADT_{eff} \cdot l \cdot b}$$

where ΔA : change in road cross sectional area due to wear in one year
l : duration of winter season for studded tire usage (days)
b : percent of the winter season when the pavement is not covered by snow/ice.

In order to compute the $AADT_{eff}$, it is customary to convert the contribution of each vehicle into a standard vehicle. If a heavy vehicle with studs wears α times the standard vehicle, and the same heavy vehicle with chains wears β times the amount worn by the standard vehicle, then the effective AADT is computed as follows (Bertelsen, Uthus and Mork, 2005):

$$AADT_{eff} = AADT \cdot \left[\%l \cdot \%p_l + \%t \cdot \left(\%p_t \cdot \alpha \cdot \frac{n_p}{4} + \%k_t \cdot \beta \cdot \frac{n_k}{4} \right) \right] \cdot f$$

where $\%l$: percentage of passenger cars
$\%t$: percentage of heavy vehicles
$\%p_l$: percentage of passenger cars with studded tires
$\%p_t$: percentage of heavy vehicles with studded tires
$\%k_t$: percentage of heavy vehicles with chains
n_p : number of wheels with studs, heavy vehicles
n_k : number of wheels with chains, heavy vehicles
f : is a factor which accounts for the number of traffic lanes.

If ΔA is measured for a two-lane road over both lanes, $f = 1$, while $f = 0.5$ for a two-lane road with equal traffic in both directions if ΔA from only one lane is included in the calculation. Data from annual traffic survey reports on the Norwegian road network (Tilstandsundersøkelser) (Muskaug, Nygaard, et al., 2003) is used for the calculations. Once the contribution from studded tire wear to the total rutting is determined, the rutting from permanent deformation in the pavement is computed by subtracting this from the total measured rut depth.

2.2. Pavement Age

It is a fact that pavements deteriorate with time. Hence, pavement age is considered in the developed model, computed from the day the road was opened to traffic after the recent major rehabilitation/overlay construction (maintenance date).

2.3. Pavement layer thicknesses

Pavement layers and their thicknesses play a very important role in distributing wheel loads to underlying subgrade. Thicker pavement structure would mean less stress to the subgrade, and subsequently less distress. In addition, variation in layer thickness can also result in variations in the structural characteristics and in-service performance of pavements (Attoh-Okine and Roddis, 1994). The selected roads are originally constructed many decades ago, and in their life time they have received a number of maintenance and rehabilitation works. As a result, these in-service pavements have a number of asphalt layers from each maintenance/rehabilitation activity over the years. These layers differ in material type, thickness and condition, having also different strength (stiffness). For a better comparison of the performance of the different pavement structures, equivalent thicknesses have been computed and used in the models. The NPRA conducted a research project "Better utilization of the bearing capacity of roads" in the period between 1990 and 1994 (Vegdirektoratet, 1994). In this project, properties of the different in-situ asphalt layers (including stiffness values) have been investigated and a database of material description and modulus values was established. These modulus values are used for the equivalent thickness computation. Using the assumptions of Odemark's equivalent thickness method (Ullidtz, 1998), the different asphalt layer thicknesses are converted to an equivalent thickness with respect to the modulus of the top layer as follows.

$$h_{eq} = h_2 \left[\frac{E_2}{E_1} \right]^{\frac{1}{3}}$$

where: h_{eq} – the equivalent thickness of layer 2 with respect to the modulus of layer 1.
h_2 – thickness of layer 2
E_2 – modulus of layer 2
E_1 – modulus of layer 1

2.4. Traffic load

Traffic loading is an important variable in predictions models. The traffic data from NVDB is the Annual Average Daily Traffic (AADT), and this is converted to Number of Equivalent 10 ton Axle Loads (N10), which is a common parameter used in the Norwegian Pavement Design standard (Vegdirektoratet, 2011). There, it is assumed that a heavy axle P (tons) has a damaging effect (equivalency factor E) in relation to a 10 ton axle which is proportional to the fourth power of the axel load ratio as follows:

$$E = (P/10)^4$$

The number of equivalent 10 ton axle loads which load the pavement for a certain period (in days) can be calculated from the actual number of heavy vehicles using the following equation:

$$N10 = f \cdot AADTT \cdot days \cdot C \cdot \bar{E}$$

where

N10	:	number of equivalent 10 ton axle loads
f	:	a factor dependent on the number of lanes (f = 1 for one lane, f = 0.5 for two-lane and f = 0.4 for four-lane roads)
AADTT	:	Average Annual Daily Truck Traffic (heavy vehicles with allowed total gross weight 3.5 tons or more)
days	:	The number of days in the period the N10 is computed
C	:	Average number of axles of heavy vehicles (C =2,4 (Vegdirektoratet, 2011))
$\bar{E}$	:	Average equivalency factor for heavy vehicle axles – it depends on the axel load distribution, which again is supposed to depend on the allowed axle load of the road ($\bar{E}$ = 0.207 for 8 tons, and $\bar{E}$ = 0.424 for 10 tons axle load limit).

2.5. Precipitation (mm) and Maximum Temperature (°C)

In addition to traffic loading, environmental conditions do also greatly influence pavement performance. Environmental data used in the models are precipitation and max temperature.

3. MODEL DEVELOPMENT

Representative roads from the Norwegian pan-European road network (Europaveg) in different geographical locations in Norway are selected. The rationales behind the selection of the roads are 1) roads which represent different geographical and climatic locations of the country, and 2) highly trafficked roads (especially near and through major cities) are avoided because they usually are maintained rather frequently, hence condition data for longer period on one particular pavement (without maintenance or rehabilitation) are usually not available. A map showing the selected roads is provided in Figure 3.

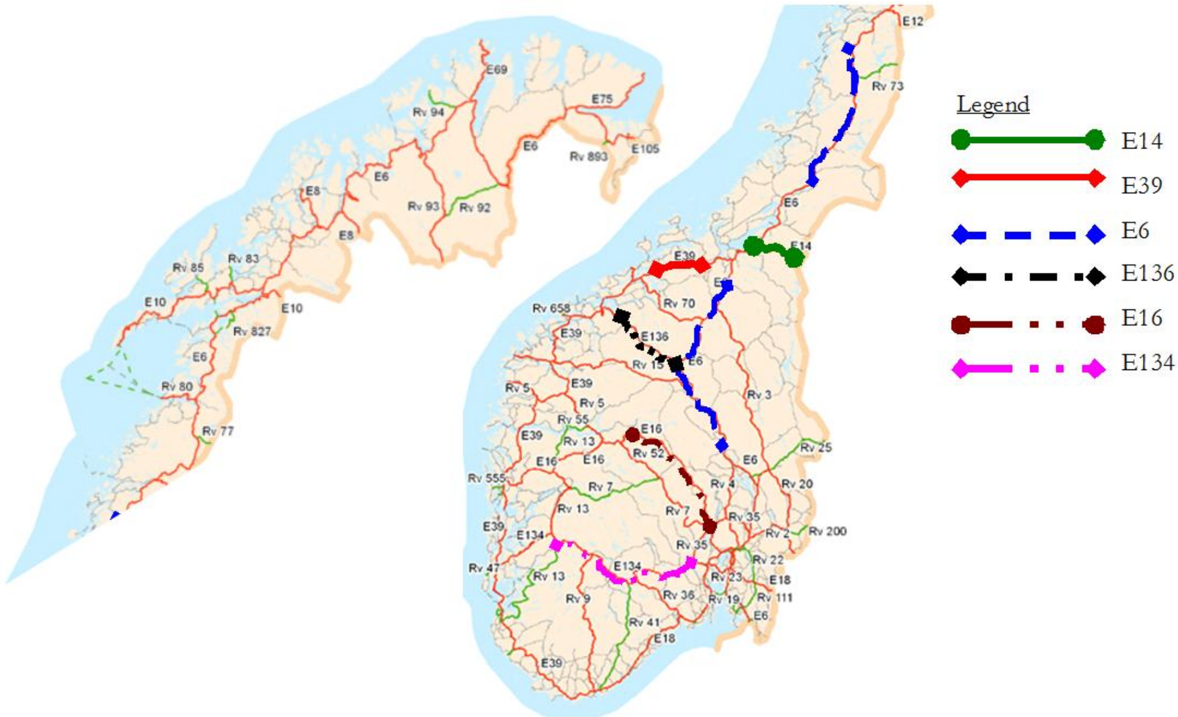

Figure 3: Map of Norway showing the selected roads

Development of pavement rutting greatly depends on the type of asphalt mix (pavement type) used. In Norway there are different types of asphalt mixes used depending on traffic amount, pavement condition (desired properties), cost, availability of materials and other local conditions (Vegdirektoratet, 2011). This paper presents the results for the stone mastic asphalt pavements (Skjelletasfalt, Ska), which again is categorized as Ska11 and Ska16 depending on the maximum aggregate size used in the mixture (11 and 16 mm respectively). After extensive and rigorous data processing, the data set is now ready for modeling. Scatter plot of the data is shown in Figure 4 and Figure 5.

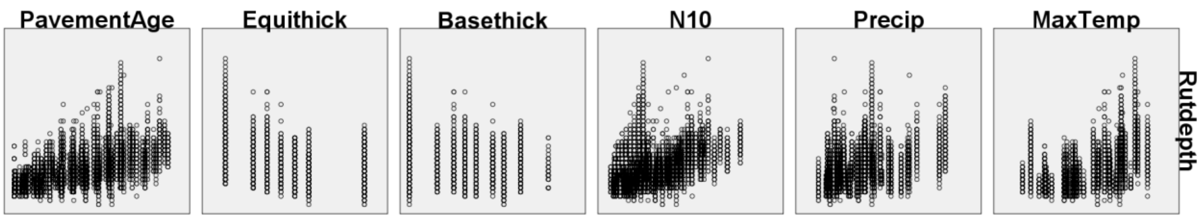

Figure 4: Scatter plot of the dataset for PavtType = Ska11

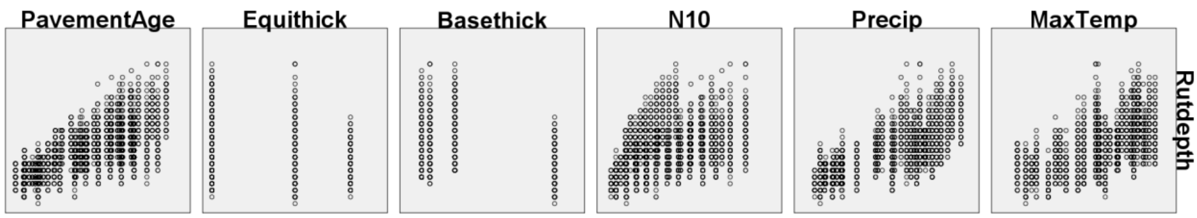

Figure 5: Scatter plot of the dataset for PavtType = Ska16

3.1. Multiple Linear Regression Models

The classical Multi - Linear Regression (MLR) is used to model the value of the dependent variable, the rut depth, based on its linear relationship with multiple predictors like pavement age, pavement layer thicknesses, traffic levels and environmental factors. In order to compare the results with that of the ANN models, a random selection of 70% of the datasets is used for the model development.

The results from the MLR analyses are shown in Table 2 and 3. Table 2 shows the coefficients (or parameters) of the best regression models and model summary. There, the N10 and MaxTemp variables are excluded from the Ska16 model, as they did not satisfy the selection criteria (*stepwise* method of variable selection). Observation of the signs of the coefficients reveals that rutting is higher on older pavements, highly trafficked roads, on pavements exposed to higher temperatures and is slightly higher in rainy areas (wet subgrade) than dry ones. Meanwhile, there is less rutting on thicker pavements. This is in perfect match with the expectations. The regression and residual sums of squares and the R^2, the coefficient of determination, show that the variation in rutting is explained 57.8% and 62.2%.

Table 2 MLR Model Coefficients and summary

Coefficients		
	Ska11	Ska16
Variable	Coefficient	Coefficient
Constant	2.201	5.886
Pavement age	.357	.458
Precipitation	.017	.018
MaxTemperature	.228	--
Equivalent thickness	-.228	-.199
Base thickness	-.089	-.046
N10	.002	--
R	.760	.789
R^2	.578	.622

Table 3: ANOVA

Pavement Type		Sum of Squares	df	Mean Square	F	Sig.
Ska11	Regression	98235.443	6	16372.574	3056.314	.000
	Residual	71810.136	13405	5.357		
	Total	170045.580	13411			
Ska16	Regression	31799.922	4	7949.981	2143.965	.000
	Residual	19311.648	5208	3.708		
	Total	51111.570	5212			

3.2. Artificial Neural Network models

An ANN is a layered network of simple processing elements called artificial neurons which exchange information via directed connections. It is a subset of artificial intelligence (which tries to simulate the biological neural network or the human brain), and it learns from experience or collected data. ANNs are recently becoming the preferred tool for many predictive applications because of their power, flexibility and ease of use. They are particularly useful in applications where the underlying process is complex, like in pavement deterioration.

ANN modeling using the backpropagation algorithm is used. IBM SPSS Neural Network software is used in this research. Here the active dataset has been partitioned into training, testing, and validation (holdout) datasets (i.e. 70% for training, 20% for testing and 10% for validation). SPSS supports two types of activation functions in the hidden layer neurons and three in the output layer neurons (SPSS, 2007). Every possible combination of activation functions between hidden and output layer neurons were tested (Taddesse, 2010). The combination of hyperbolic tangent function for hidden layer neurons and the sigmoid function for the output layer neuron gave the least amount of errors and the best goodness-of-fit.

For determining the optimum number of units in the hidden layer, a trial-and-error procedure was adopted, whereby the Neural Network training program was run by varying the number of units in the hidden layer, and the performance of the models was assessed using error and goodness-of-fit criteria. Details of the selected optimum ANN architecture and model summary are provided in Table 4 and Table 5.

The R^2 values between the actual and model predicted rut depth values given in the model summary table (Table 5) show that up to 78% of the variation in pavement rutting is explained by the ANN models. This is quite satisfactory considering that the data source is routinely collected field data, and the high uncertainty usually associated with pavement deterioration process. From the ANN training and testing, synaptic weight (or ANN parameter estimate) matrices are derived. They represent the knowledge abstracted from the dataset, which can be programmed for application of the models.

Table 4 Optimum ANN architecture information

		Ska11	Ska16
Input Layer	Covariates	N10 Basethick Equithick PavementAge MaxTemp Precip	PavementAge N10 MaxTemp Equithick MaxTemp Precip
	Number of Units[a]	6	6
	Rescaling Method for Covariates	Standardized	Standardized
Hidden Layer(s)	Number of Hidden Layers	1	1
	No. of Units in Hidden Layer 1[a]	13	10
	Activation Function	Hyperbolic tangent	Hyperbolic tangent
Output Layer	Dependent Variable	Rut depth	Rut depth
	Rescaling Method for Dependents	Normalized	Normalized
	Activation Function	Sigmoid	Sigmoid
	Error Function	Sum of Squares	Sum of Squares
Architecture topology		6-13-1	6-10-1

a. Excluding the bias unit

Table 5 Model Summary

		Ska11	Ska16
Training	Sum of Squares Error	15.943	14.944
	Relative Error	.217	.259
Testing	Sum of Squares Error	4.667	4.585
	Relative Error	.220	.295
Holdout	Relative Error	.239	.279
Goodness-of-fit (R^2)		0.783[a]	0.741[a]

a. Goodness-of-fit computations are based on the training dataset.

4. MODEL EVALUATION

Predictive models are often evaluated by testing their prediction accuracy using a part of the dataset that is not used in their development, which is called out-of-sample dataset.

4.1. Validation of the MLR models

As mentioned in section 3.2, 70% of the dataset was used for the model development, in order to compare the results with the ANN models. Like for the ANN models, the MLR models are validated with a 10% out-of-sample datasets, whereby rut depth predictions using these datasets are compared with the actual values. The results of this task are depicted in Table 6, and Figure 6 and Figure 7. The coefficient of determination or R^2 values between the actual and predicted rut depths (using the validation dataset) are between 54.1% and 59.5%. Comparing the results from the validation dataset with the results from the training dataset (Table 6), the performance of the MLR models in predicting rut depth using the 10% out-of-sample dataset is satisfactory, with relative change in R^2 values of 6% and 4%.

Table 6: Comparison of results of the training and validation of MLR models

Pavement Type	MLR								
	R^2			*RMSE*			*MAPE*		
	TRA	VAL	*RC*	TRA	VAL	*RC*	TRA	VAL	*RC*
Ska11	0.578	0.541	-6%	2.313	2.473	7%	23.7%	24.3%	3%
Ska16	0.622	0.595	-4%	1.925	2.086	8%	23.5%	22.9%	-2%

TRA – *Training dataset* VAL – *Validation dataset* RC – *Relative change*
RMSE – root mean square error *MAPE - mean absolute percentage error*

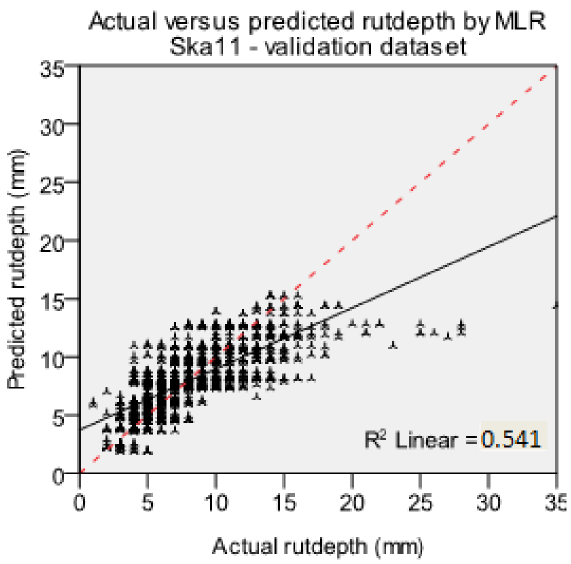

Figure 6: Actual versus predicted rut depth using validation dataset by MLR –Ska11

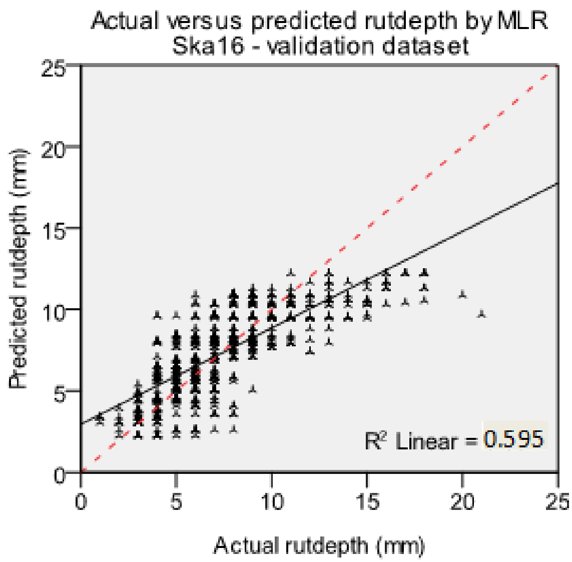

Figure 7: Actual versus predicted rut depth using validation dataset by MLR –Ska16

4.2. Validation of the ANN models

For validation of the ANN models 10% of the dataset was set aside during the training and testing phases (refer section 3.2). Predictions of rut depths are carried out using this dataset, the results of which are depicted in Table 7, and Figure 8 and Figure 9. The R^2 values are 76.1% and 72.1%. Comparing the results from the validation dataset with the results from the training dataset (Table 7), the performance of the ANN models in predicting rut depth using the 10% out-of-sample dataset is satisfactory, with relative change in R^2 values being 3%.

Table 7: Comparison of results of the training and validation of ANN models

Pavement Type	ANN								
	R^2			*RMSE*			*MAPE*		
	TRA	VAL	*RC*	TRA	VAL	*RC*	TRA	VAL	*RC*
Ska11	0.783	0.761	-3%	1.659	1.785	8%	15.2%	15.6%	3%
Ska16	0.741	0.721	-3%	1.593	1.732	9%	18.0%	18.1%	1%

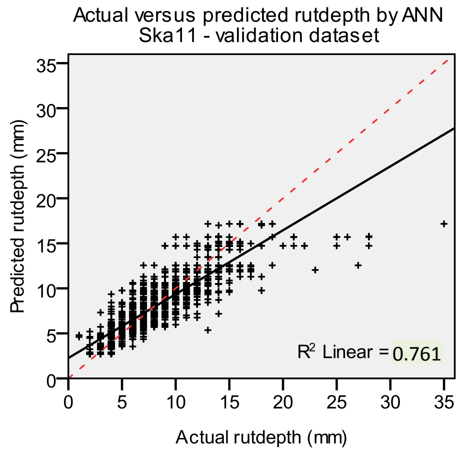

Figure 8: Actual versus predicted rut depth using validation dataset by ANN-Ska11

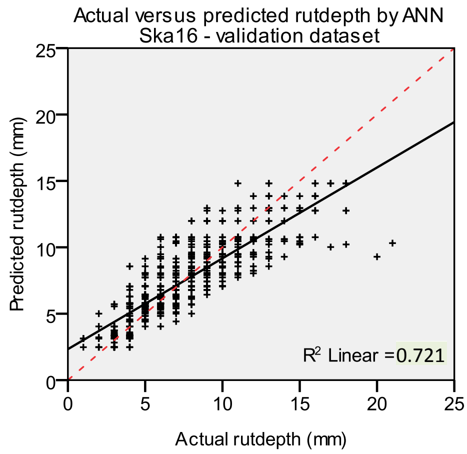

Figure 9: Actual versus predicted rut depth using validation dataset by ANN-Ska16

5. Comparison of MLR and ANN models

Figure 10 and Figure 11 show scatter plots of actual versus predicted rut depth values using MLR and ANN models for the Ska11and Ska16 pavements respectively. The R^2, RMSE and MAPE values using the training datasets are summarized in Table 8, together with the relative difference in performance prediction capability between the models from the two methods. Evidently, the ANN models have produced results that are better than those from MLR (with a relative increase in R^2 values from the ANN models of 35% and 19%). With regard to the error parameters, the ANN models have also produced considerable decrease in RMSE and MAPE values (with a relative decrease in RMSE of up to 28% and in MAPE values up to 36%). This comparative study with respect to prediction ability clearly reveals that the ANN models predict the rut depth with greater accuracy than MLR models do.

Table 8: Comparison of the prediction ability of MLR and ANN models - training dataset.

Pavement Type	MLR			ANN			Relative change		
	R^2	RMSE	MAPE	R^2	RMSE	MAPE	R^2	RMSE	MAPE
Ska11	0.578	2.313	23.7%	0.783	1.659	15.2%	35%	-28%	-36%
Ska16	0.622	1.925	23.5%	0.741	1.593	18.0%	19%	-17%	-23%

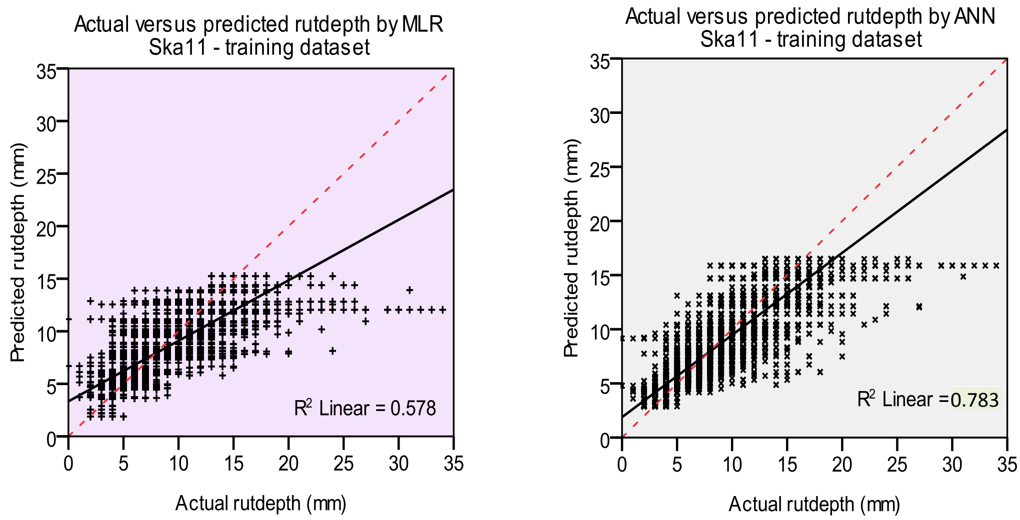

Figure 10: Scatterplots of actual versus predicted rut depth using training dataset by MLR and by ANN, *Ska11*

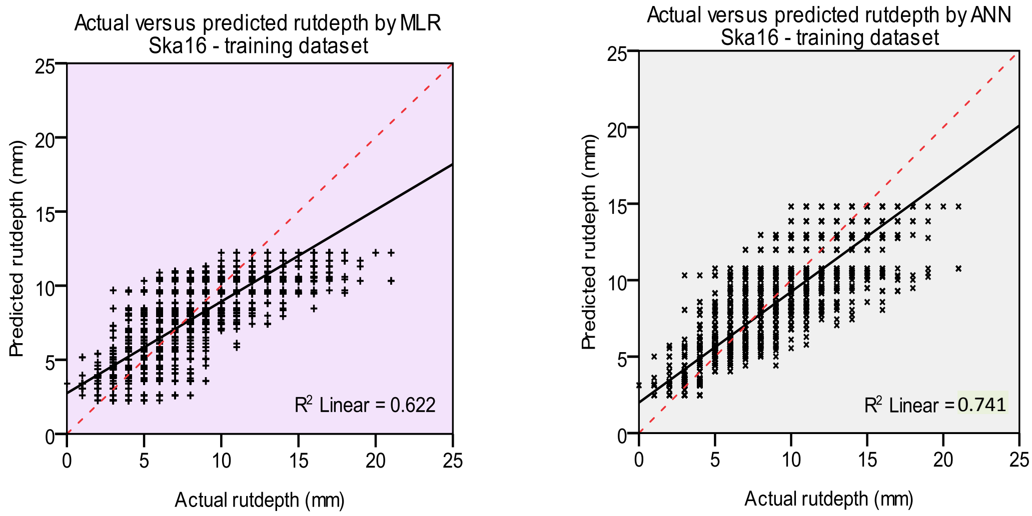

Figure 11: Scatterplots of actual versus predicted rut depth using training dataset by MLR and by ANN, *Ska16*

6. CONCLUSION

Using the Norwegian national road databank (NVDB), rut depth prediction models for to stone mastic asphalt mixture types (Ska11 and Ska16) using MLR and ANN modeling techniques are developed. An important goal was to use the intelligent artificial neural network modeling technique and check its predicting capability versus multiple linear regression method. The following important conclusion can be drawn: 1) pavement condition data routinely collected from in-service roads is a good source of data for development of pavement performance prediction models, and 2) the use of the innovative modeling technique of ANN has shown to improve the prediction capability. A slight improvement in the accuracy of modeling is important because it results in a large economic effect.

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