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Using Neural Networks for Pavement Rolling Resistance

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Abstract
All pavements contribute to the rolling resistance of vehicles. For passenger cars, the pavement influence is limited to the surface properties, but heavy trucks are influenced by the deformation, the internal damping, and non-elastic behavior of the pavement materials involved. Previous studies have been addressing the pavement type, the material type and various stages of compaction. Recently, even the effects of curling slabs on rolling resistance was assessed. As sustainable pavements are now becoming a requirement from road authorities, it is important to have access to calculable parameters of energy losses during use, and not only from construction. The present paper addresses some of the input parameters needed to assess rolling resistance losses for pavements in general and rigid pavements in particular, by using neural network techniques. The results can be used for the decision-making in either bidding processes or strategic planning.

Introduction

Traffic operating costs are important for the optimization of transportation. Road roughness affects the vehicle speed, rider comfort, vehicle wear, and rate and severity of accidents. All these items can be attributed to costs. Most road authorities now run Pavement Management Systems (PMS), which are relying heavily on user costs. These data and their associated costs are used for asset valuation purposes as well. In addition to actual costs for e.g. fuel, in recent years the carbon footprint is associated as an additional cost to road transportation previously ignored.

For the highly competitive transport sector, the vehicle operating costs are more important than ever. Much attention concerns the engine and tire technology, but relative little research focus on the pavement contribution to sustainability. Thus, further investments in infrastructure could very well be justified if such result in lower emissions. For instance, comparative tests on different pavement types show that the truck rolling resistance generally is lower on rigid pavements, but there is a variability due to other external factors, such as temperature. By sampling and storing time histories from Falling Weight Deflectometer (FWD), testing it is possible to generate load-deflection data sets. Thus, it is possible to estimate the pavement contribution to truck rolling resistance.

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Research Significance

The pavement contribution to the rolling resistance requires sampling of the FWD load and deflection histories. All sensors have to be calibrated over the duration of the pulse. Further, software has to be developed to process the data in reasonable time. Obviously, it will take a long time to analyze large data sets, which may discourage further processing. The present study aims at finding data readily available for estimating the dissipation work without analyzing time histories. If feasible, large data sets on layer moduli or deflections can be analyzed for rolling resistance right from the database source.

Objective

The present paper is addressing the pavement contribution to rolling resistance in pavements. The objective is to look at variables that seem to influence the energy dissipation the most through sensitivity analysis by training neural networks. The input parameters are load, deflections, backcalculated structural parameters such as E-moduli and strains. The output is the dissipation energy derived from load-deflection time history data.

Scope

The pavement type analyzed is rigid pavements only. The test is limited to available data collected during late summer and fall conditions, thus seasonable variation is not considered.

Background

Vehicle fuel consumption is depending on acceleration, wind resistance, and rolling resistance. The wind resistance is a function of the vehicle design, front area, and wind speed. The rolling resistance is depending on the tire friction, internal friction for engine and drive train, plus a component consisting of deforming the surface. A large part of the losses attributed to rolling resistance is from the tires interacting with the pavement. Thus, the tire industry has made a lot of research in this area optimizing the design of tread and wheel design. Pavement engineers have also contributed to the research by looking at the surface texture. There is a tradeoff with other desired parameters such as low noise and good friction to consider. In addition, macro-texture and roughness affect the fuel consumption also. At a full-scale pavement test facility, driverless trucks needed 4% less fuel after the track was resurfaced, (Mitchell). The influence of the pavement profile including joints on rolling resistance is rather easy to determine with a truck suspension model, but the losses within the pavement layers and soil are much more difficult to assess.

Tests involve careful measurements of truck fuel consumption in the field on several different pavement types, (Taylor et al., Hultqvist). These tests are not entirely conclusive, much due to factors hard to control, such as the aforementioned wind speed and direction, hill gradients, temperature fluctuations et cetera.

To overcome the problems with wind speed an FWD can be used to mimic the load from a passing truck. The load pulse is designed to correspond to a certain speed, but as the surface deformation is recorded as well, it is possible to derive some interesting dynamic properties. Figure 1 shows a 50-millisecond load pulse and the corresponding response from deflection sensor D_0 at the center of the loading plate. The maximum deflection is .3 mm, for the 50 kN maximum load.

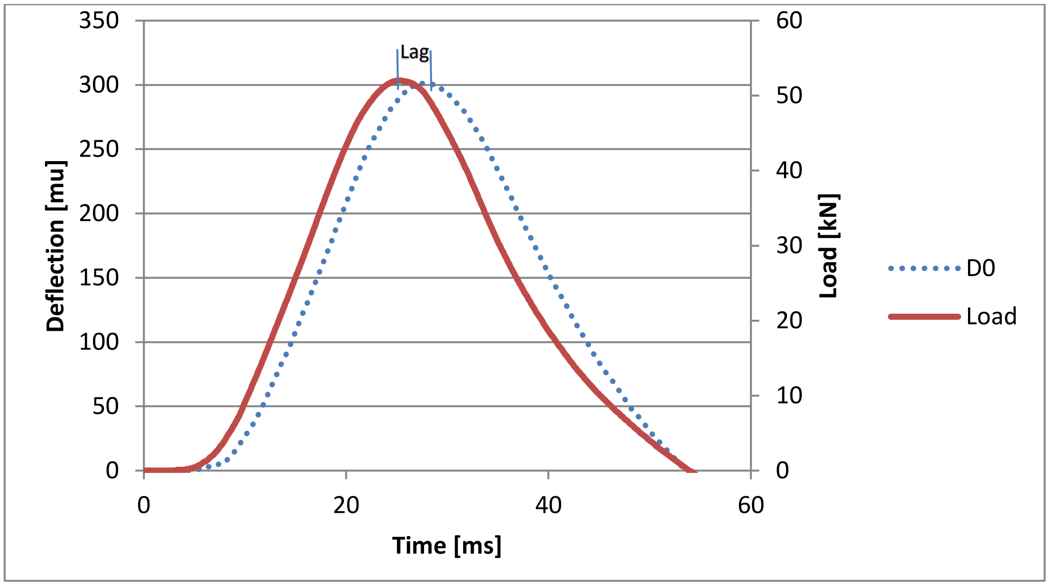

Figure 1. Time history plot of a load and deformation.

If plots are made as a load-deflection diagram, the energy attenuation losses in the pavement layers and the soil can be derived. Figure 2 illustrates a semi-rigid and flexible pavement center deflection response for two 50 kN drops. Note that these load-deflection graphs do not represent hysteresis directly. However, the magnitude of the work has been calibrated to the truck-fuel-consumption test results derived at the site, (Hultqvist, Lenngren 2009). The economic implications from choosing pavement type were further investigated by (Fäldner).

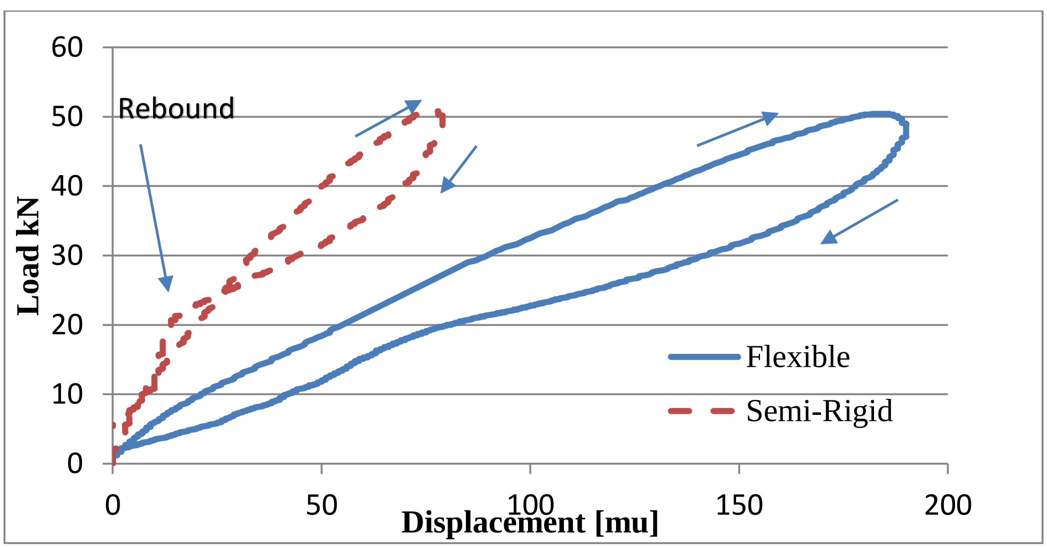

Figure 2. Semi-rigid and flexible pavement load-displacement diagram.

The dissipation in Figure 2 was derived to .4 Nm and 2.2 Nm for the two different pavement types respectively. These values are common for high volume roads resting on relatively stiff subgrades. Over the years, the dissipation in many different pavement structures have been assessed. One of the present authors, (Lenngren 2014), investigated the dissipation of upward curling in concrete slabs. It was found to be significant enough to be included in the overall assessment of rolling resistance. There were also tests during construction and for compaction. Lack of compaction would show up as additional dissipation as much of the impact work is consumed rearranging the unbound granular material.

Figure 3 shows a test from a failed mining road. Iron ore trucks travelled the road before all layers were in place, and the road deteriorated fast. The dissipated work is about 100 times greater than for a rigid road. It illustrates the large variability of various roads, and that there is a need to minimize the dissipation for sustainability.

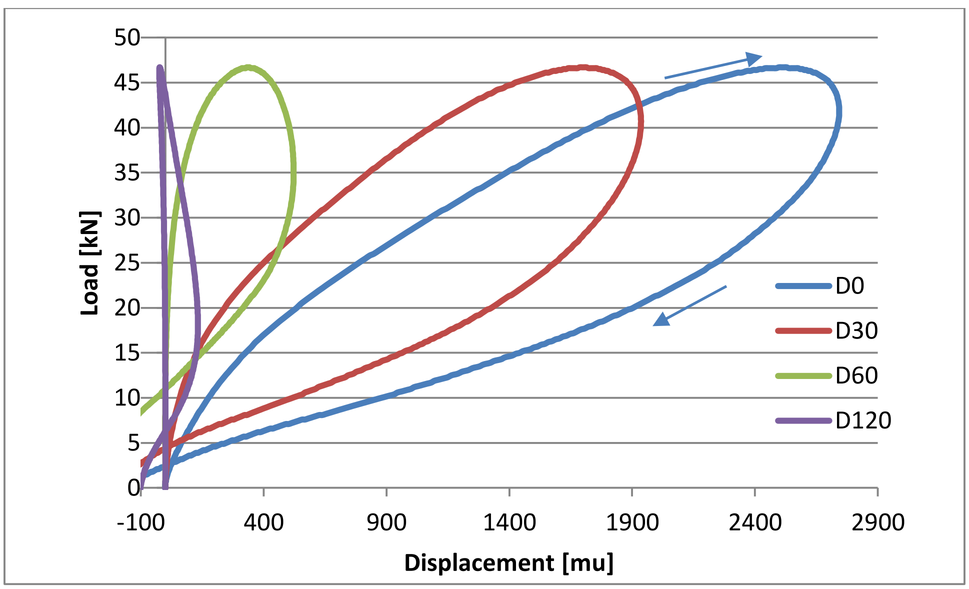

Figure 3. Load-Deflection diagram from a mining Road.
Work is about 44 Nm.

Neural Networks

Artificial neural networks (ANN), or just neural networks (NN), are a form for machine learning software system inspired by biological neural networks and used to model and estimate results that are function of a large number of inputs, with complex or even unknown relationship. It has special algorithms that mimic neurons and work together exchanging messages between each other to give importance to the input data in form of weight, making neural networks capable to adapt to learn. For practical purposes, the neural networks can be used to create black box-like models that store a given knowledge that can be used to identify how the inputs are interacting to create the desired output and to evaluate similar situations [Schalkoff, 1997].

Building a Data Base and Using Neural Networks for Assessing Dissipation

In the previous studies, rather straightforward calculations of FWD time history data were utilized to derive the pavement contribution of various pavement types and soils. However, over the past thirty years, there are many FWD test sites with collected data, which do not contain the calibrated deflection time histories. In addition, for new road construction, it is not possible to acquire such data unless rather expensive test sections are constructed. Thus, by building a data base containing layer properties and known designs with measured dissipation, it should be possible to determine some expected dissipation at the planned stage. The data would help in designing sustainable pavements and decreasing the carbon footprint altogether. A bonus effect would be to access what parameters have the most influence of the dissipation.

Data used for the present study

The data used for this study were collected in the year 2010 on the motorway E20 near the city of Eskilstuna, Sweden by an experienced team, with a dynamically calibrated FWD device. The moduli were backcalculated based on the deflection data and materials thicknesses with the CLEVERCALC 4.0 software, using elastic linear materials in the model.

Deflections were read at the distances from the FWD loading plate center shown in Table 1. For each section, ten tests were performed, i.e. ten drops, with the FWD parked in the same position. The load was varied at three load levels, repeated twice as can be seen in Table 2.

Table 1. Deflections distances

Deflection	Distance from the loading plate center
d0	0 cm
d1	20 cm
d2	30 cm
d3	45 cm
d4	60 cm
d5	90 cm
d6	120 cm

The sections in the present study consists of a 550 mm granular subbase. A 150 mm cement treated base on which a 200 mm Portland Cement Concrete slab is resting. Tests were done in a center slab position. The sections are going through cuts and embankments as well.

Energy dissipation calculation

The energy dissipation was derived from time history load-deflection loops, by an incremental procedure in the software TimeH developed earlier for the previous studies. The dissipation was calibrated to truck-fuel-consumption tests on different pavement types, (Lenngren 2009, Hultqvist.)

Evaluation of energy dissipation based on deflections

Neural networks were used to evaluate the energy dissipation based on deflection data, temperature, load and drop height, which are numeric inputs. Ten load drops were done at every section and the drop number was used in the NN model as a class input.

The data set has 130 cases, 104 (80%) were picked by random for the model generation and the remaining 26 (20%) were used for testing. Table 2 is showing the data for the first tested section.

Table 2. Sample data used for the deflection versus energy dissipation model

Input data											Output
Drop #	Drop Height	Load (kN)	Temp. (C)	Deflections (0.001 mm)							Dissipation (Nm)
				d0	d1	d2	d3	d4	d5	d6	
1	3	53.2	10.1	58	54	52	50	47	40	33	3.6
2	2	42.8	10.1	46	42	40	39	36	31	26	3.3
3	3	54.1	10.1	58	54	51	49	46	40	33	3.4
4	4	73.9	10.1	80	75	71	67	64	56	46	1.6
5	2	42.4	10.1	46	43	40	38	36	31	26	3.5
6	3	53.5	10.1	58	54	50	49	46	40	33	4.9
7	4	73.8	10.1	80	75	71	67	64	55	46	8.4
8	2	42.3	10.1	46	42	40	39	36	31	26	5.9
9	3	53.4	10.1	58	54	50	48	45	39	33	0.4
10	4	73.8	10.1	80	75	72	67	64	55	46	1.0

The NN generate black-box models, which cannot be described in the form of an equation. It should be evaluated according to its outputs over the training and test data sets. Figure is showing the generated model predictions against the actual values for the training data while Figure shows the same model used with unseen data, the testing data set.

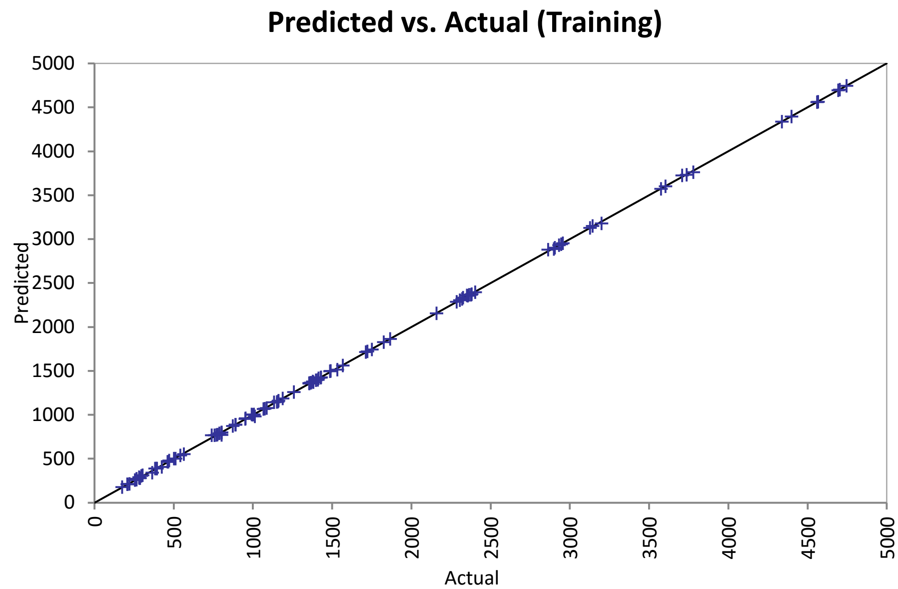

Figure 4. Dissipation prediction versus actual values. Based on the deflection data for the training data set

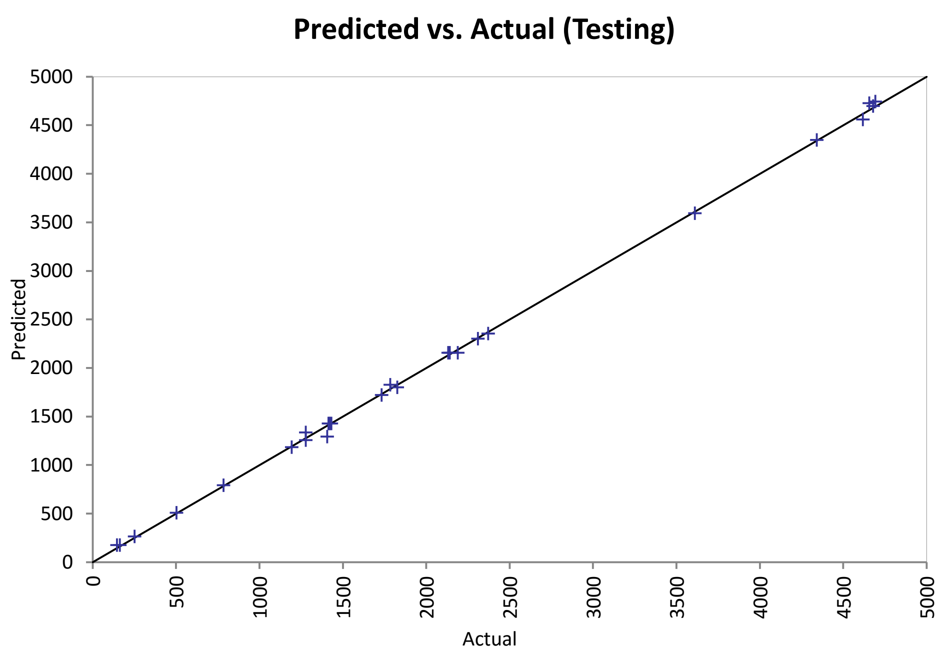

Figure 5. Dissipation prediction versus actual values. Based on the deflection data for the testing data set

The sensitivity analysis was performed to evaluate the relative variable impacts, i.e., how important every input is for the output (energy dissipation) construction. This analysis is based on the built model with the training data set. Figure shows that deflections 0, 4, 1, 6, 2 and 5 are the best inputs for the energy dissipation calculation. Other data, including deflection 3, drop number, temperature, load and drop height are not relevant, i.e., by ignoring or removing them from the data set will lead to a better model rather than processing them together.

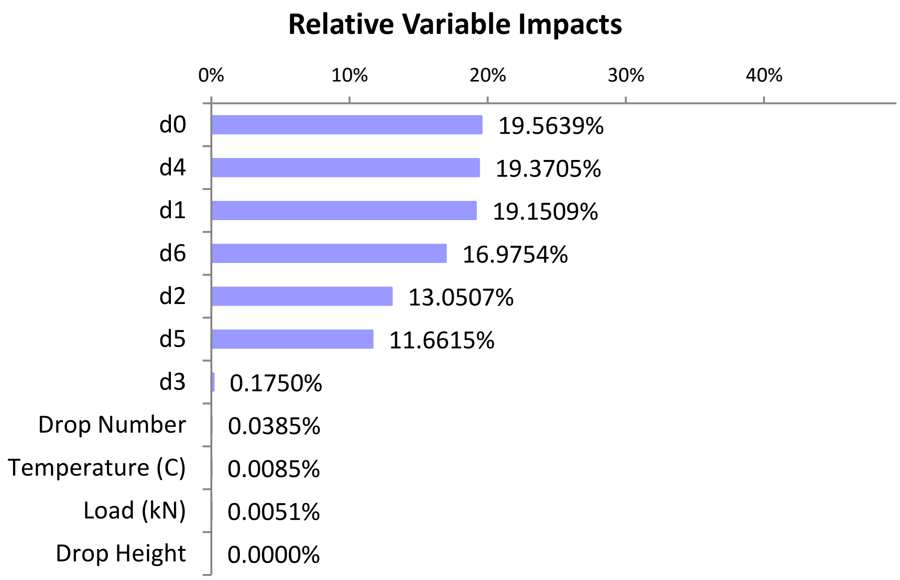

Figure 6. Sensitivity analysis for dissipation prediction with base on the deflection data

Evaluation of energy dissipation based on deflections and modulus

Another NN model was generated to evaluate the deflections and modulus data as input for the energy dissipation calculation (output).

The used input variables for the modeling were the deflections 0 to 6, the temperature, the modulus for the four layers, the drop number and the load, with the energy dissipation as output. The 130 cases data were also split by random between training (80%) and testing (20%). Table 3 is showing the data for the first tested section. Note that the backcalculated PCC layer is kept fixed at 40 000 MPa.

Table 3. Sample data used for the modulus and deflection versus energy dissipation model.

INPUTS														OUTPUT
Drop number	Deflections (0.001 mm)							Modulus (MPa)				Temp. (C)	Load (kN)	Dissipation (Nm)
	d0	d1	d2	d3	d4	d5	d6	E(1)	E(2)	E(3)	E(4)			
1	58	54	52	50	47	40	33	40000	28996	123	472	10.1	53.2	3.6
2	46	42	40	39	36	31	26	40000	31562	187	428	10.1	42.8	3.3
3	58	54	51	49	46	40	33	40000	30763	209	413	10.1	54.1	3.4
4	80	75	71	67	64	56	46	40000	31069	225	394	10.1	73.9	1.6
5	46	43	40	38	36	31	26	40000	26102	369	376	10.1	42.4	3.5
6	58	54	50	49	46	40	33	40000	31274	247	389	10.1	53.5	4.9
7	80	75	71	67	64	55	46	40000	29556	237	395	10.1	73.8	8.4
8	46	42	40	39	36	31	26	40000	30755	186	422	10.1	42.3	5,9
9	58	54	50	48	45	39	33	40000	26687	438	363	10.1	53.4	0.4
10	80	75	72	67	64	55	46	40000	28767	211	407	10.1	73.8	7.1

The model was generated after 65 interactions and its performance against the actual values for the training data set is shown in Figure 7. The model used to predict unseen data, i.e. the testing data set, is shown in Figure 8.

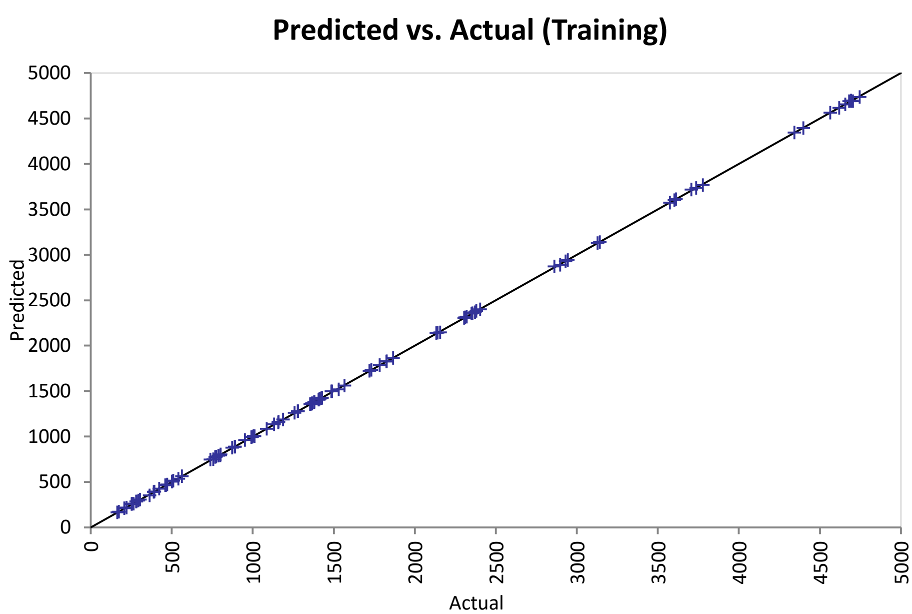

Figure 7. Dissipation prediction versus actual values with base on the deflection and modulus data for the training data set

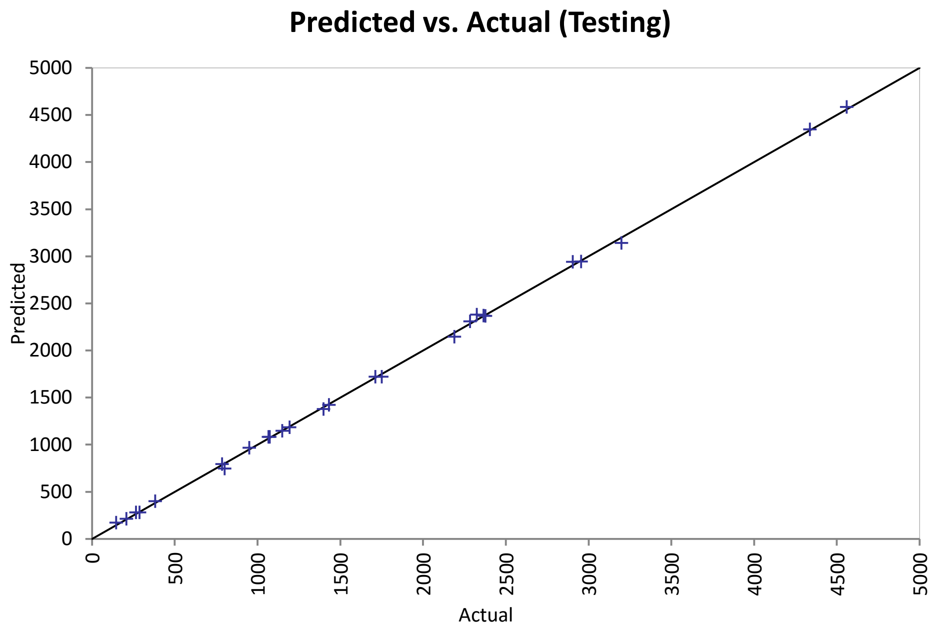

Figure 8. Dissipation prediction versus actual values with base on the deflection and modulus data for the testing data set

The relative variable impacts are shown in Figure 9. When exposed to use both deflection and modulus data, the NN discovered that using just deflections would lead to a better result, giving little relevance for the modulus and other data. The NN once again gave no relevance to the deflection d3.

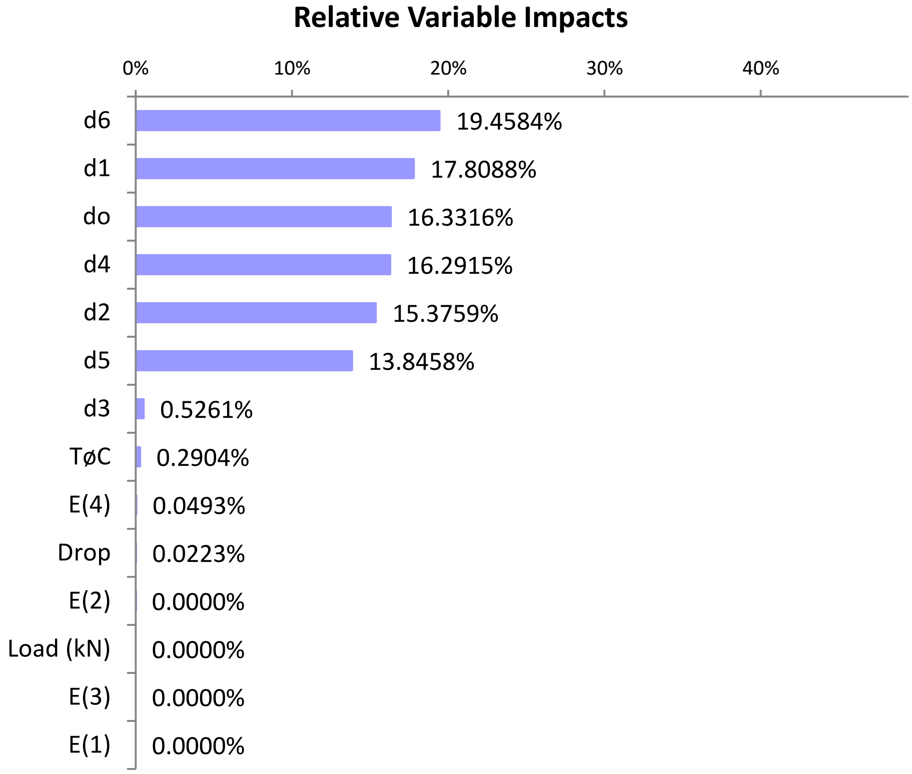

Figure 9. Sensitivity analysis for dissipation prediction with base on the deflection and modulus data

Evaluation of energy dissipation based on modulus

As part of this exploratory study the NN were enforced to generate the model just with modulus, temperature, load and drop number as input, and keeping the energy dissipation as output. Again, the same data set, split into training (80%) and testing (20%) was used.

Table 4 is showing the data for the first tested section.

Table 4. Sample data used for the modulus and deflection vs. energy dissipation model

INPUTS							OUTPUT
Drop #	Modulus				Temperature (C)	Load (kN)	Dissipation (Nm)
	E(1)	E(2)	E(3)	E(4)			
1	40000	28996	123	472	10.1	53.2	3.63
2	40000	31562	187	428	10.1	42.8	1.73
3	40000	30763	209	413	10.1	54.1	3.03
4	40000	31069	225	394	10.1	73.9	8.01
5	40000	26102	369	376	10.1	42.4	1.63
6	40000	31274	247	389	10.1	53.5	2.94
7	40000	29556	237	395	10.1	73.8	7.38.
8	40000	30755	186	422	10.1	42.3	1.45
9	40000	26687	438	363	10.1	53.4	2.80
10	40000	28767	211	407	10.1	73.8	7.57

The model was generated after 75 interactions only. Figure 10. and 11 are showing a model with a slight drop in performance for both, training and testing data sets, when compared with the model generated with deflections only.

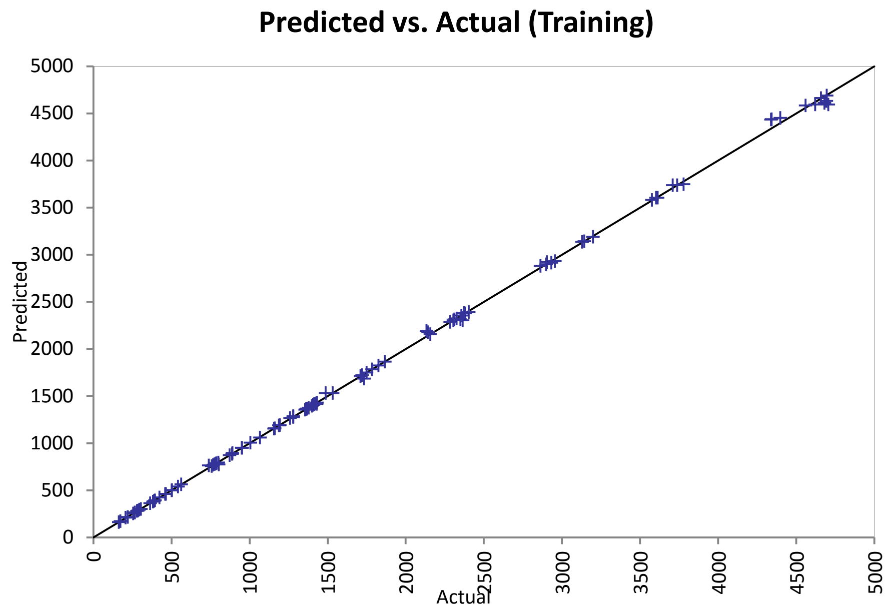

Figure 10. Dissipation prediction versus actual values. Based on the modulus data for the training data set

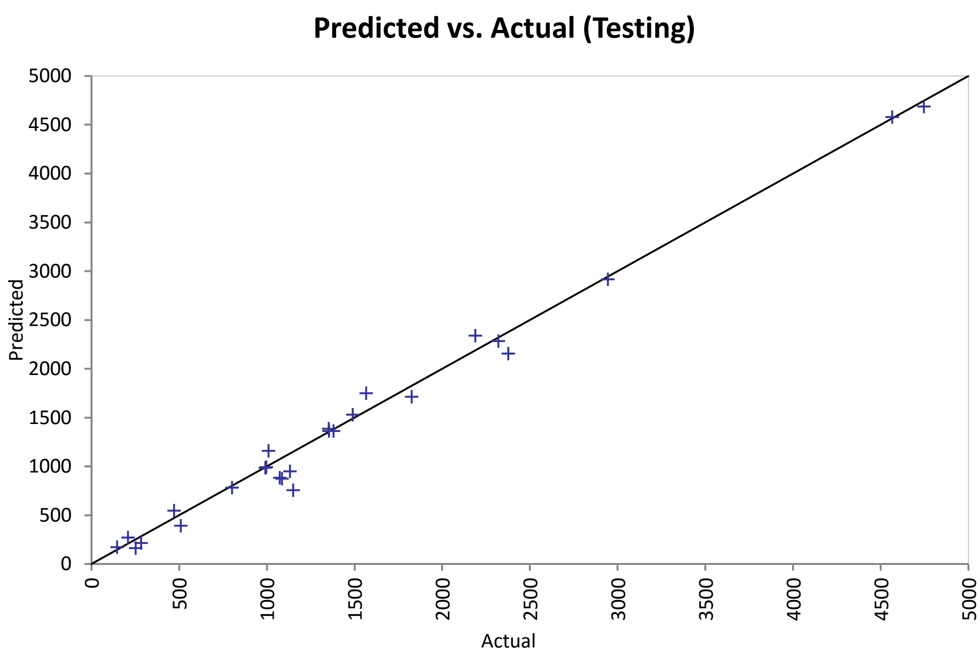

Figure 11. Dissipation prediction versus actual values. Based on the modulus data for the testing data set

The sensitivity analysis is showing that the subgrade modulus (E4) and the load are almost the only required variables for the best prediction. See Figure 12.

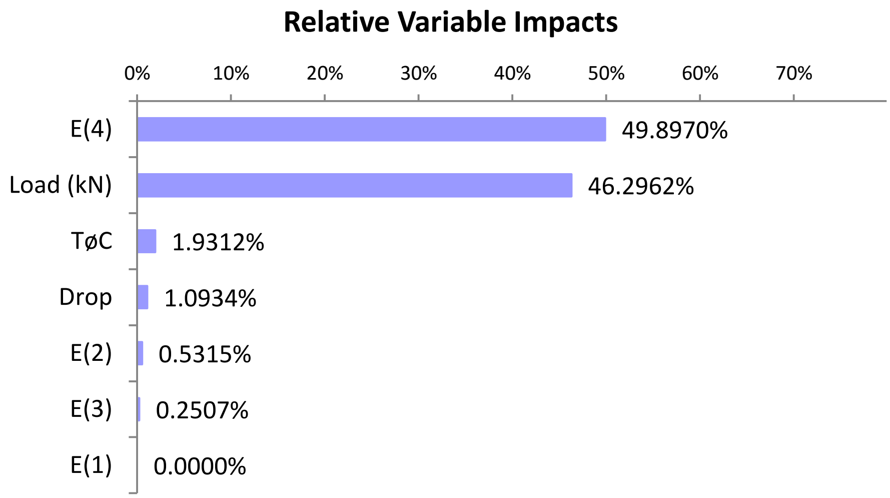

Figure 12. Sensitivity analysis for dissipation prediction with base on the modulus data

Discussion

There is dissipation in pavements due to a number of reasons. There are inertia, compaction, strain energy leading to fatigue, visco-elastic and non-linear plastic properties just to mention a few. For rigid pavements, the deformation in the unbound materials is relatively small, so most of the dissipation work occurs in the subgrade. This in turn also governs the deflection measured on the surface. Thus, one might surmise that there will be a correlation between deformation and dissipation. In addition, other parameters could be considered as noise, likely to degrade a direct correlation study. In the present study, all test basins were from a center slab position, so no effects of curling were prevalent. If the tests had progressed during a summer day, including late afternoon, with changing degrees of curling, the results could have been inconclusive.

The deflection d_3 at three load plate radii is not relevant for the energy dissipation prediction, something that was confirmed by the deflection only model, and deflection plus modulus model as well. There is no obvious explanation, but it may be related to its distance from the loading plate combined with these specific materials thicknesses. Looking at shape of the deflection basin, the d_3 position is near the inflection point of the curve. This is the location where the change of deflection along the radius from the load is greatest.

Conclusions

The present study shows the internal pavement energy dissipation can be successfully modeled with neural networks, with very consistent results for both, training and testing data sets.

The deflections data comprise a better input to calculate the energy dissipation than the modulus, providing a more accurate result for both, training and testing data sets.

For the characteristics of the tested pavement, the number of drops is not relevant. There is no need to perform 10 drops on every section. A smaller number of drops will suffice for a faster and cheaper sampling. However, this may not apply for new pavements being subjected to compaction by traffic a.k.a. Phase I Rutting.

The temperature was found to be irrelevant, as expected. For all performed tests, it was almost constant, with variability between 9.8 and 10.4 degree Celsius only. The tests were done mid-slab with little bending due to gradients.

For the model with the deflection data, the loads are not important according to the NN. It seems as the deflections are providing information good enough to construct a robust model and the load consideration will degrade its accuracy.

For the model with modulus data only, the subgrade modulus and load are the most important variables. This was expected because, for the tested sections, the materials and thicknesses are constant.

When allowed to use both, deflections and modulus data, the NN concluded that the consideration of just deflection will lead to a better model and left no relevance to modulus. Thus, there is no practical purpose considering the modulus.

The findings and conclusions are valid for the used data set, where the pavement thicknesses were constant and the temperature was almost constant on all stations. However, within reasonable variation, the thickness will also affect the deflection and the dissipation in the same direction. The temperature may contribute to curling, which also increases the input and output in the same fashion.

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