Estimating New Road Rolling Resistance Using Neural Networks

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Estimating new road rolling resistance using neural networks

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ABSTRACT: All pavements infer rolling resistance. Heavy trucks are influenced by the deformation, the internal damping, and non-elastic behavior of the pavement materials involved. Earlier studies have been addressing the pavement type, the material type and various stages of compaction. In par with manufacturing and house construction, sustainable pavements are now becoming a requirement from authorities. There are advanced computer programs to assess the greenhouse gasemissions from construction, but less emphasis have been set on the user stage. Hence, it is important to access calculable parameters of energy losses that will occur during use. The present paper addresses some of the input parameters needed to assess rolling resistance losses for pavements in general and new flexible pavements in particular, by using neural network techniques. The results can be used for the decision-making in either bidding processes or strategic planning.

1 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 often are relying on user costs. The output is used for asset valuation as well. In addition to actual operating costs, the carbon footprint is included as an additional cost to consider, that was previously ignored. From a physical standpoint, energy as fuel is needed to accelerate the vehicle and to gain potential energy by climbing hills. In addition, there are energy losses due to air resistance and rolling resistance, which generate heat. The latter are unwanted effects, which should be kept to a minimum.

Rolling resistance consists of several components. Air resistance and rolling resistance together comprise the force needed to maintain the coasting speed. The rolling resistance in turn can be divided into transmission loss, tire hysteresis, tire-pavement interaction and pavement deformation. The present paper deals with pavement deformation only.

For the highly competitive transport sector, the vehicle operating costs are more important than ever. Much attention of reducing these costs concerns the engine and tire technology, but relative little research focus on sustainable pavements. 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, there is a way to assess the pavement contribution to truck rolling resistance in a controlled mode with no influence of wind and other external factors.

2 OBJECTIVE

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

3 SCOPE

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

4 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/pavement 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 investigating the surface texture. There is a trade off between low rolling resistance and other wanted parameters such as low noise and sufficient friction during wet conditions. In addition, pavement macro-texture and roughness affect the fuel consumption as well. At a full-scale pavement test facility, driverless trucks needed 4% less fuel after the track was resurfaced (Mitchell 2000). The influence of the pavement profile on rolling resistance is rather easy to determine with a truck suspension model, but the losses within the pavement layers and soil are more challenging to assess.

To find out the pavement contribution to rolling resistance careful measurements of truck fuel consumption in the field on several different pavement types have been made.(Taylor *et al.,* 2001) (Hultqvist 2010). 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 a 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 0.3 mm, for the 50 kN maximum load.

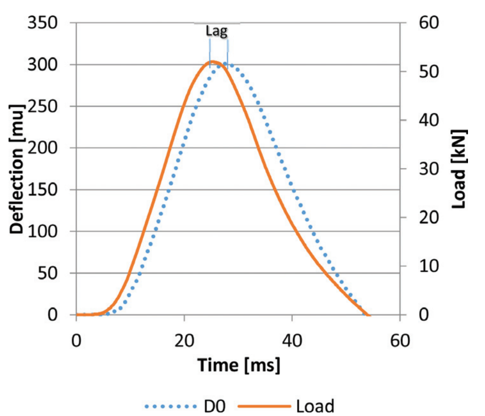

Figure 1. Time history plot of a load and deformation.

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 a test site (Hultqvist 2010) (Lenngren 2009). The economic implications from choosing pavement type were further investigated by Fäldner (Fäldner 2012).

The dissipation of energy in Figure 2 was derived to 0.4 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 are also tests during construction and for compaction.

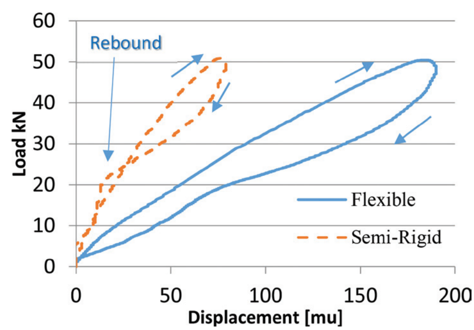

Figure 2. Semi-rigid and flexible pavement load-displacement diagram.

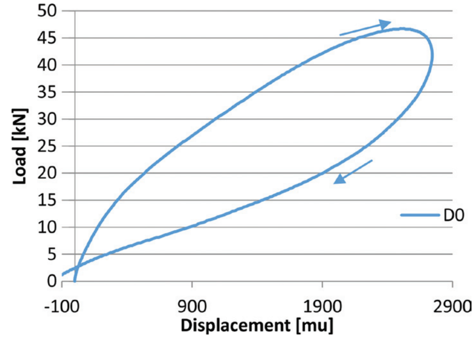

Figure 3. Load-deflection diagram from a mining road showing a dissipated work of about 44 Nm.

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.

5 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 relationships. 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).

5.1 *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 expected dissipation at the planning stage. The data would help in designing sustainable pavements and decreasing the carbon footprint altogether. A bonus would be to determine parameters that have the most influence of the dissipation.

5.2 *Data used for the present study*

The data used for the present study were collected in the fall of 2010 for a survey on new pavement bearing capacity in Sweden. Two sites were chosen. Motorway E18 near the city of Västerås, and Highway 68 about 120 km further to the North. The layer moduli were back calculated based on the deflection data and layer thicknesses with the CLEVERCALC 4.0 software, using linear elastic materials in the model.

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

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 and Table 3.

5.3 *Energy dissipation calculation*

The energy dissipation was derived from time history load-deflection loops, by an incremental procedure in the software Time H developed earlier for the previous studies. The dissipation was calibrated to truck-fuel-consumption tests on different pavement types (Lenngren 2009) (Hultqvist 2010).

The sections in the E18 site consists of a 770 mm granular sub base. An 80 mm unbound base on which 200 mm Asphalt Concrete (AC) (in three lifts) is laid. The Hwy 68 site is designed for less traffic. The design consists of 590 mm of subbase, 80 mm of unbound base and 130 mm of AC layers.

Tests were done in the right-hand wheel path. The E18 site was tested in the evening with a pavement temperature of about 15°C. The Hwy 68 site was tested during the day in light rain with a temperature of about 10°C.

5.4 *Evaluation of energy dissipation based on deflections*

Neural networks were used to evaluate the energy dissipation based on deflection data (D0 – D6), air and pavement temperatures, load (force), drop number, lane number and thicknesses for asphalt concrete (h1) and granular layer (h2). Ten load drops were done at every test section.

The data set contained 369 cases, 295 (80%) were picked by random for the model generation and the remaining 74 (20%) were used for testing and model quality control.

Table 2 is showing the data parameters for the first tested section with 10 cases.

The NN generate black-box models, which cannot be described in the form of an equation.

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

INPUTS														OUTPUT
							Deflections (m)							
h1 (cm)	h2 (cm)	Lane #	Drop #	Air Temperature (^{0}C)	Pavement Temperature (^{0}C)	Force (kN)	D0	D1	D2	D3	D4	D5	D6	Energy dissipation (Nm)
20	85	1	1	14.6	19	52.2	289	257	234	201	174	128	98	8
20	85	1	2	14.6	19	41.9	211	188	172	147	126	96	72	4.46
20	85	1	3	14.6	19	53.1	269	240	219	188	164	122	95	7.36
20	85	1	4	14.6	19	72.9	368	328	303	257	224	168	127	14.23
20	85	1	5	14.6	19	41.4	208	184	170	147	126	96	72	4.28
20	85	1	6	14.6	19	52.3	265	236	215	185	162	121	94	7.06
20	85	1	7	14.6	19	72.7	363	323	299	254	222	166	127	13.69
20	85	1	8	14.6	19	41.8	210	186	169	147	127	97	73	4.32
20	85	1	9	14.6	19	52.5	264	235	215	186	163	121	95	7.01
20	85	1	10	14.6	19	72.9	361	322	298	253	221	166	127	13.56

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

INPUT										OUTPUT
							Modulus			
h1 (cm)	h2 (cm)	Lane #	Drop #	Air Temperature (^{0}C)	Pavement Temperature (^{0}C)	Force (kN)	E(1) (MPa)	E(2) (MPa)	E(3) (MPa)	Work (Nm)
20	85	1	1	14.6	19	52.2	7541	162	125	8
20	85	1	2	14.6	19	41.9	8065	177	137	4.46
20	85	1	3	14.6	19	53.1	7918	189	130	7.36
20	85	1	4	14.6	19	72.9	8394	170	137	14.23
20	85	1	5	14.6	19	41.4	8394	170	137	4.28
20	85	1	6	14.6	19	52.3	7975	193	128	7.06
20	85	1	7	14.6	19	72.7	8453	178	136	13.69
20	85	1	8	14.6	19	41.8	8453	178	136	4.32
20	85	1	9	14.6	19	52.5	8231	192	128	7.01
20	85	1	10	14.6	19	72.9	8536	180	136	13.56

It should be evaluated according to its outputs over the training and test data sets. Figure 4 is showing the generated model predictions against the actual values for the training data while Figure 5 shows the same model applied to unseen data, the testing data set. The symmetry line is plotted in both figures.

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 was based on the built model with the training data set. Figure 6 shows that Deflections 6 (D6) and zero (D0) are the best inputs for the energy dissipation calculation with some minor relevance for air temperature. Other data, including the remaining deflections, drop number, load (force), pavement temperature, lane number and pavement thicknesses 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.

5.4.1 *Evaluation of energy dissipation based on modulus*

Another NN model was constructed to evaluate the energy dissipation based on modulus for asphalt concrete, granular layer and subgrade (E1, E2, E3), air and pavement temperatures, load (force), FWD drop number, lane number and pavement thicknesses of asphalt concrete (h1) and granular layer (h2). Again, ten load drops were done at every section and the data was split by random between training (80%) and testing (20%). Table 3 is showing the data parameters for the first tested section. Figure 7 is showing the generated model predictions against the actual values for the training data and Figure 8 for unseen data.

Again the sensitivity analysis was performed to evaluate the relative variable impacts based on the built model. Figure 9 shows that the loading force and modulus for subgrade (E3) are the most important factors for the energy dissipation calculation. Modulus for the granular layer (E2)

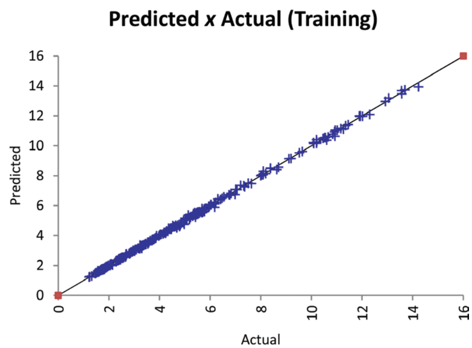

Figure 4. Dissipation prediction versus actual values based on the deflection data for the training data set.

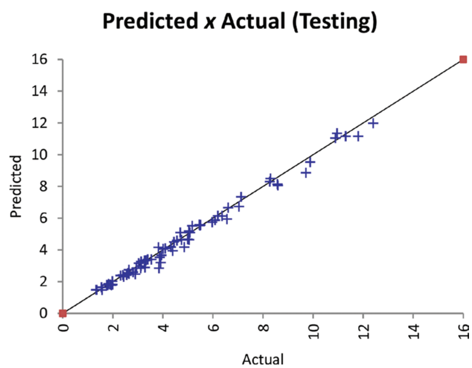

Figure 5. Dissipation prediction versus actual values based on the deflection data for the testing data set.

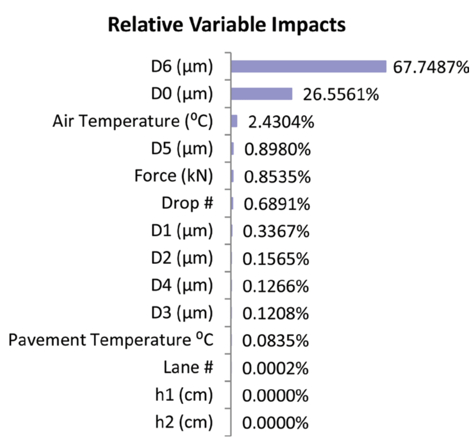

Figure 6. Sensitivity analysis for dissipation prediction with base on the deflection data.

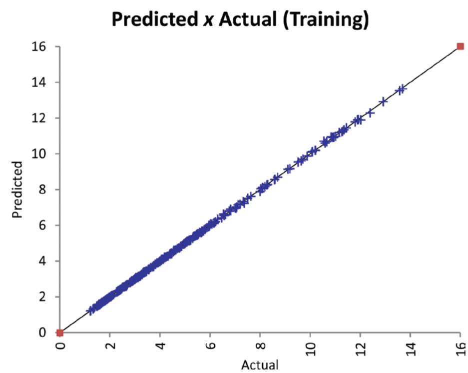

Figure 7. Dissipation prediction versus actual values based on modulus for the training data set.

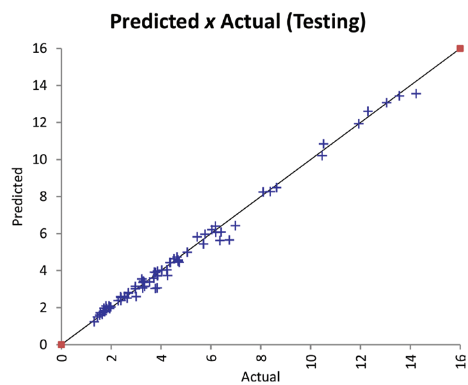

Figure 8. Dissipation prediction versus actual values based on modulus for the testing data set.

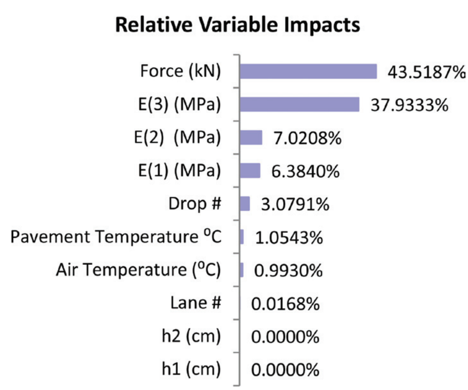

Figure 9. Sensitivity analysis for dissipation prediction with base on the modulus.

and asphalt concrete (E1), and drop number have some marginal relevance. Other data, including pavement thicknesses and lane number are not very relevant.

6 DISCUSSION

There is dissipation for loads exerted on pavements due to a number of reasons. There are inertia, inadequate compaction, strain energy leading to fatigue, viscous-elastic and non-linear plastic properties just to mention a few.

In a similar study for rigid pavements, the deformation in the unbound materials was found to be relatively small, so most of the dissipation work occurs in the subgrade, (Lenngren and Salini 2016). Comparing with deflections only the outermost D6 sensor also showed the best correlation with the dissipation. If the modulus was incorporated, the subgrade modulus gave the second best correlation after the load.

However, the new flexible pavement study presented in this paper was not as consistent as the corresponding rigid one, and that may be explained by the asphalt concrete viscoelastic properties. This means that the energy is dissipated from the top down. Thus, we have to model not only a geometrical spread of the load, but also factor in the dissipated energy right from the surface. As for NN solutions, maybe binder rheology properties could be used as an input to improve on the situation.

The temperature range was small, only about five degrees Celsius. It gave only a weak correlation. The pavement layer thicknesses did not show any relationship either, but a larger range could maybe improve the correlation. Thicknesses have also a natural variability very hard to detect, that the neural networks will sense and consider for the modeling.

7 FURTHER WORK

As sustainability is becoming an important factor for all public investments, the authors believe that the proposed model will improve on the greenhouse gases emissions calculations for highways at the planning stage. Yet, we have been looking at rigid and new flexible pavements. Other pavement types could be studied in the same fashion, including gravel and flexible surfacing, which are probably influenced even more by the subgrade and unbound layer properties. For flexible pavements, binder properties could maybe improve on the regressions and further advice on which recipe to use for improving on sustainability.

8 CONCLUSIONS

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

The subgrade properties seem to give the best prediction and thus are the most important factors for energy dissipation.

The temperature was found to be almost irrelevant, which was not expected. The available range was small though, 9.9 to 15.2 degrees Celsius for air temperature, and 13 to 19 degrees Celsius for pavement temperature. That small range may suppress the outcome on the analysis.

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 pavement material properties did not vary much and the thicknesses have a limited range, 13 and 20 cm for asphalt concrete layer, and 76 and 85 cm for granular layer respectively.

The findings and conclusions are valid for the used data set, where the pavement thicknesses were in a rather limited range and the temperature was almost constant within either of the two sites. With this NN approach now well proven as viable and effective, further research can be done by considering a more complex mix of situations including variable pavement thicknesses, binder properties, a broad range of temperatures and other inputs like seasonal variation.

There are many older data sets sampled with maximum deflection only. Hence, the present method provides a way to assess rolling resistance without time history data. In addition, the method could provide feedback during operation, such as interactive sampling frequency needs.

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