RMMS
Road marking management system
Deliverable 2: Deterioration of road markings
## Project
Road marking management system

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## Report title
Deliverable 2: Deterioration of road markings

## Summary
The scope of this report was to test the hypothesis that road marking functional parameters can be derived from a series of explanatory variables. Work in this report can conclude that the hypothesis has been proven with a statistically significant result. Explanatory variables in this report concluded that models can be built with machine learning models in order to be retrained as new data comes in. Models made has a coefficient of determination of between 0.4 to 0.7 and standard deviations span from 10-20%. This suggests that a significant correlation has been found that could be used in order to predict road marking functionality in asset management planning. It also suggests that such models could get better by training with new data, testing of new explanatory variables not tested in this report or testing of other models in order to explain the dependant factors. A general conclusion is also that it seems applicable to use a machine-learning approach in order to explain road marking deterioration – which is not a linear phenomena. Road owners is therefore recommended to keep a database with at least the placeholders in this report, and also to adopt machine models when estimating road marking performance. Deterioration in asset management system is normally categorized and then expected to be a linear phenomena. Master curves could be used from machine models in order to make those categorizations and make possible to add linear functions.

For retroreflection dry, the number of individual datapoints where sufficient for analysis of all participating countries. For Sweden and Norway, also for wet retroreflection, daytime luminance and friction. In Denmark, this data came from the project called ROMA, and data gathered so far in that project is not sufficient yet for analysis, but will likely be in a few years time. Although it is not necessary that the use of deterioration models for anything else than retroreflection dry is necessary, as this factor stands for the absolute majority of the disapproved cases – hence this parameter tends to be the first one to fail in all cases.

In further work, it is recommended that systematic gathering of explanatory and descriptive data in this study is implemented in the respective countries asset management strategy. It has been proven quite hard to find road marking material specific
data. Thickness, which ought to be one very important factor, is not gathered in a way that can be traced to a specific coordinate. Plowing and salting, which is also a significant factor, should also be targeted.

The work here is to be considered as a first step. It has been proven that machine learning models can be used in order to with a statistical certainty describe functional development of road markings over time. If databases can be constructed as in this document, and the machine model adopted in this work can be implemented – models can continue to improve over time. As road markings are a living material and are not constant over time, model work will never be completed but always evolve. That is why keeping databases up to date on a yearly basis, complemented by road marking performance data, is a key factor in success of using deterioration models for predicting future maintenance and budget needs.

**Keywords**
RMMS, Road marking management system, deterioration, machine learning

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36
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Background and purpose

Management systems are available in many shapes and variants for multiple disciplines. Road operational management systems are not an exception. One critical tool for any management system is the possibility to monitor outcome of different solutions based on functional capacities today, modelled into a near future to predict where efforts need to be done in order to achieve a certain standard. With that said, it is one thing to set a specific standard for what to achieve and in what extent. It’s a totally different thing to be able to monitor this standard and to calculate how this will change in the near future. The ability to monitor and calculate future costing is also crucial in order to make a life cycle costing model, or LCC. It is not a secret that validated degradation models for road construction is a very complex task, and the outcome will always be a hypothesis test, where the hypothesis can be proven right, or wrong. Also, the work will never finish. A first model can be fine-tuned infinitely using more and more data, while presumptions and conditions change with time. This is to be considered in the following work.

In Nordic countries, pavement management systems are commonly used to predict when to repair and resurface based on certain functional standards. It is therefore also of interest to achieve the same for road markings, where today, models for degradation and specific standards does not exist in the same way.

The purpose with this paper is

- To describe previous work that has been done regarding deterioration models in the field of road markings and the lessons learned.
- To propose a statistic model to verify for road marking applications
- To propose variables to be analysed– in what extent and with what method.
- To calibrate and validate a model for deterioration based on the above

The method used for created such a model has been through the use of Machine Learning.

The hypothesis is that one can, in a statistically significant way, describe how functional parameters change with time for road marking applications. This hypothesis will not be analysed in this paper, but the method for answering it will be described.
Previous studies

In 2005, the state of Iowa department of transportation (DOT) studied a management program for state road marking maintenance. This work did not scope to analyse any type of degradation models, but rather to inventory the states conditions of retroreflectivity amongst markings and to make a cost-efficient plan to manage the re-painting of road markings with low functional capabilities. Some interesting facts came through that might be interesting. The average snowfall was monitored over the state which directly affects the amount of snowploughing, which is known to significantly affect road marking functionality. Also, edge rutting maintenance was found to have deterministic impact on marking reflectivity, which suggests that actions like this is to be considered for any type of degradation model if applicable. Conclusions led to a suggestion of type of marking to use dependant on life expectancy, rural/urban/interstate location, AADT, velocity limit and lane (Hawkins 2005).

![Figure 1](image1.png)

Figure 1. Longitudinal Pavement Marking application matrix for Iowa department of transportation. From Hawkins et. al (2005).

A pilot study in Norway (Lundkvist et al, 2009) was a first attempt to analyse how road markings change with time. The study was quite simplified, with marking follow-up after one year. But the study showed a very good correlation between calculated and measured retroreflective properties, although the short period of time tested made the outcome quite unusable. The work although describes in what manner a model could be constructed.

\[
Y_{ijk} = \mu + \alpha_i + \beta_j + \gamma_k + (\alpha \times \beta)_{i,j} + (\alpha \times \gamma)_{i,k} + (\beta \times \gamma)_{j,k} + (\alpha \times \beta \times \gamma)_{i,j,k} + \varepsilon \quad (\text{eq. 1})
\]

The Y-variable represents the response variable which will be monitored; in this case the functional properties of road marking. \(\mu\) is the intercept and \(\varepsilon\) the error term. The \(\alpha\), \(\beta\) and \(\gamma\) is the explanatory variables monitored. Explanatory variables might interact, hence the multiplication of all thinkable variables. The explanatory variables where then included or excluded in the equation by using a set of data and checking the corresponding significance level (\(p < 0.05\)) and also the effect size (\(\eta^2\)) (Lundkvist et. al, 2009).
The above mentioned worked was followed up in the “Beste Praksis Vegoppmering”, by Johansen (2013). The scope of this project was not primarily to develop any degradation models, but to monitor life expectancies of markings to make LCC-cost analysis for the Norwegian Road Agency. A general lesson from this work was that a significant portion of the sections chosen where unexpectedly re-painted within the follow-up cycle and therefore also rejected in analysis (Johansen 2013).

The outcome of this project was a recommendation of different road marking applications based on type of line, AADT and if the action is classified as new-laying or repair.

Table 1, outcome of proposed actions on road markings (type I only). From Johansen (2013). E= extruded thermoplastics, S=sprayplastics, M = paint combined with thickness in mm.

<table>
<thead>
<tr>
<th>Veg</th>
<th>Nylegging</th>
<th>Reparasjon</th>
</tr>
</thead>
<tbody>
<tr>
<td>Midlinje v/ÅDT</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 - 300</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>300 - 1000</td>
<td>E 2.0</td>
<td>S 1.5</td>
</tr>
<tr>
<td>1000 - 1500</td>
<td>E 2.0</td>
<td>E 2.0</td>
</tr>
<tr>
<td>1500 - 3000</td>
<td>E 2.0</td>
<td>E 2.0</td>
</tr>
<tr>
<td>3000 - 5000</td>
<td>E 3.0</td>
<td>E 2.0</td>
</tr>
<tr>
<td>5000 - 15000</td>
<td>E 3.0</td>
<td>E 2.0</td>
</tr>
<tr>
<td>&gt; 15000</td>
<td>E 3.0</td>
<td>E 3.0</td>
</tr>
<tr>
<td>Kantlinje v/ÅDT</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 - 300</td>
<td>S 1.0</td>
<td>M 0.4</td>
</tr>
<tr>
<td>300 - 1000</td>
<td>S 1.0</td>
<td>M 0.4</td>
</tr>
<tr>
<td>1000 - 1500</td>
<td>S 1.5</td>
<td>S 1.0</td>
</tr>
<tr>
<td>1500 - 3000</td>
<td>S 1.5</td>
<td>S 1.5</td>
</tr>
<tr>
<td>3000 - 5000</td>
<td>S 1.5</td>
<td>S 1.5</td>
</tr>
<tr>
<td>5000 - 15000</td>
<td>E 3.0</td>
<td>E 2.0</td>
</tr>
<tr>
<td>&gt; 15000</td>
<td>E 3.0</td>
<td>E 3.0</td>
</tr>
</tbody>
</table>

Another survey is described in Lundkvist (2014). A significant difference is that the the response variable maximum value was not known, hence only relative differences were analyzed. With a sorting function, ordinary national surveys could be used to isolate sections that were not re-painted and re-measured yearly from 2011 to 2013. Retrorreflective properties were monitored, and significance analysis pointed that variance analysis of road type and if the marking was profiled or not were interesting. Six equations were made for three cases of different road types and profiled/not profiled. The data-amount was rather small and the data-loss big mostly due to re-building of sections, but regression analysis showed promising results. Interesting was that ANOVA studies showed that only road-type and if the marking was profiled or not showed significance, which of course also could be affected by the smaller data-amount.

Table 2, regression equations where year is number of years after application. From Lundkvist (2014)

<table>
<thead>
<tr>
<th>Road Type</th>
<th>Profiled (Y/N)</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>HW</td>
<td>N</td>
<td>$R_L=260-31^*\text{YEAR}$</td>
</tr>
<tr>
<td></td>
<td>Y</td>
<td>$R_L=332-46^*\text{YEAR}$</td>
</tr>
<tr>
<td>2+1 type road (sep.)</td>
<td>N</td>
<td>$R_L=255-27^*\text{YEAR}$</td>
</tr>
<tr>
<td></td>
<td>Y</td>
<td>$R_L=333-41^*\text{YEAR}$</td>
</tr>
<tr>
<td>2-lane road (not sep.)</td>
<td>N</td>
<td>$R_L=243-27^*\text{YEAR}$</td>
</tr>
<tr>
<td></td>
<td>Y</td>
<td>$R_L=267-41^*\text{YEAR}$</td>
</tr>
</tbody>
</table>

The regression constant of the above equations is high and span from $0.931 \leq r \leq 0.991$. 
The work was followed in 2015, but the dataloss was now too high. Although a significant connection could be proven between type of road marking (edge line, lane line etc.) and the age of the road marking since application (Lundkvist, 2015).

Another example is from Finland. Thermoplastic and sprayplastic road markings to a total length of 6016 km were followed up by measurement during a up to six year cycle in the region of Vaasa. Markings where not re-applied during this period. Only the parameter RL(dry) where used in the surveys. By monitoring the amount of road marking volume under demands for different materials, a probabilistic model was set up for the three different materials. This also means that the only variable used as explanatory was time. On the y-axis, the probability of meeting or exceeding the life expectancy on the x-axis is described. (Äijö, 2011)

Conclusions

A general conclusion from the above stated work is that it seems possible to analytically describe road marking functional development using statistical analysis and a significant amount of data. The biggest challenge is to apprehend all data needed for analysis and also to make sure the studied objects remain untouched during the whole life expectancy. This can for certain durable markings like thermoplastics be a significant amount of years. It is not unusual that some markings lasts for three to five seasons without any re-painting. During this period, no re-surfacing or any other measures affecting the roadmarking can be taken. This suggests that one have four fundamental approaches in how to select objects for surveying:

1) A selection of sections that are newly painted is selected for measurement continuously. This means that measurements must correspond to pavement programs in the specific country. The positive side is that the new functional value is known. The backside is that the number of objects could be rather small, and the probability of data-loss high.

2) From national surveys, a selection of sections that is newly paved for five years back in time are selected for surveying, with the assumption that no measures have been taken during that time. The positive side is that the amount of data is high, the backside is that the functional value from when the marking was new is not known, and it could be hard to make any conclusions.
3) With the help of a database, all info needed is gathered regarding administrative info and functional measurements yearly. This gives data that is secured and reliable which will make the probability of a functioning degradation model higher. The downside is that this will take time, as no such database yet exists.

4) The Nordic test fields are used to analyse road marking development. The upside is that all needed data exists, the downside is that it might not be representable road markings as to what will be normally distributed nationwide later.

All the above options are reasonable, although in this work has been targeted on option 1. The best option, although, would be the 3rd one, but no such database yet exists.
Proposed variables

In this chapter, variables likely to describe road marking functionality will be stated.

Response parameters

The state-of-the-art report regarding mobile survey of road marking parameters made in this project gives us the possible parameters to monitor. With this given, it is likely that some parameters will be neither applicable for degradation nor dimensioning for when marking properties are too low. Friction (SRT/PFT) is a good example of that. Friction will likely be increased with time, giving no practical use of monitoring. Some parameters correlates, like retroreflection dry and wet, also QD and β. The first component to try to predict will be retroreflection in dry circumstances, as it is the most implemented one in any system. The other functional parameters will come after.

Table 3, response parameters (P) available from Nilsson (2017)

<table>
<thead>
<tr>
<th>System / Parameter</th>
<th>Functional parameters</th>
<th>Geometric parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RL_D</td>
<td>RL_W</td>
</tr>
<tr>
<td>Delta LTL-M</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Vectra Ecodyn 3</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Vectra Ecodyn 30</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>RoadVista Laserlux G7</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Ramböll RMT3</td>
<td>X</td>
<td>X(^2)</td>
</tr>
<tr>
<td>RMS Retro-Tek M</td>
<td>X</td>
<td>X(^1)</td>
</tr>
<tr>
<td>Zehntner ZDR 6020</td>
<td>X</td>
<td>X(^1)</td>
</tr>
<tr>
<td>EasyLux Dynamic</td>
<td>X</td>
<td>X(^1)</td>
</tr>
</tbody>
</table>

*1) RL\(_W\) based on measurement on systematically watered road marking, e.g. separate measurement not simultaneously with other parameters

*2) Not directly measured, modelled from background factors correlating with the specific parameter

*3) NTY only (Night-Time Yellow)

Available response variables are given by type of system. In this case, Ramböll RMT will be used as the supplier of response parameters.

The above summarizes in four distinguished parameters that are plausible for monitoring in a system, which are shown in the table below. Each parameter is also given by an interval rate, meaning the smallest scale in which the correspondent parameter is averaged if possible and a typical range.
Table 4, response parameters (P) in the RMMS system

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Greatness</th>
<th>Interval rate</th>
<th>Typical range</th>
</tr>
</thead>
<tbody>
<tr>
<td>(RL_{(dry)})</td>
<td>Nighttime visibility in dry conditions</td>
<td>mcd/m²*lux</td>
<td>Each 100 meters</td>
<td>0-2000</td>
</tr>
<tr>
<td>(RL_{(wet)})</td>
<td>Nighttime visibility in wet conditions</td>
<td>mcd/m²*lux</td>
<td>Each 100 meters</td>
<td>0-400</td>
</tr>
<tr>
<td>(Q_{0})</td>
<td>Daytime visibility in dry conditions</td>
<td>mcd/m²*lux</td>
<td>Each 100 meters</td>
<td>0-360</td>
</tr>
<tr>
<td>(C)</td>
<td>Coverage</td>
<td>Percent</td>
<td>Each 100 meters</td>
<td>0 - 100</td>
</tr>
</tbody>
</table>

Explanatory variables

The explanatory variables are parameters that will be used in the regression analysis and therefore also in prognostic models, given that significance exists. Thinkable explanatory variables that are thought to affect functional properties over time are described in the table below, which are taken from previous studies and a workshop conducted with the project members.

Table 5, explanatory variables (F) used in the RMMS model

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Index j</th>
</tr>
</thead>
<tbody>
<tr>
<td>Marking age</td>
<td>(years) from application</td>
<td>1</td>
</tr>
<tr>
<td>Thickness</td>
<td>(mm) at application</td>
<td>2</td>
</tr>
<tr>
<td>Material</td>
<td>Type of material (thermoplastic, sprayplastic or paint)</td>
<td>3</td>
</tr>
<tr>
<td>Road type</td>
<td></td>
<td>4</td>
</tr>
<tr>
<td>Road class</td>
<td>Road classification. Based in AADT</td>
<td>5</td>
</tr>
<tr>
<td>Profile</td>
<td>Profiled or not profiled marking</td>
<td>6</td>
</tr>
<tr>
<td>P-class</td>
<td>From the Nordic certification system</td>
<td>7</td>
</tr>
<tr>
<td>Linetype</td>
<td>Edge line, lane line or center line</td>
<td>8</td>
</tr>
<tr>
<td>Salting</td>
<td>Yes or No</td>
<td>9</td>
</tr>
<tr>
<td>Plowing</td>
<td>Yes or No</td>
<td>10</td>
</tr>
<tr>
<td>Curvature</td>
<td>Curvature radius</td>
<td>11</td>
</tr>
<tr>
<td>Contractor</td>
<td></td>
<td>12</td>
</tr>
<tr>
<td>AADT</td>
<td>Daily average traffic intensity, averaged over one year</td>
<td>13</td>
</tr>
<tr>
<td>Coordinates</td>
<td>Geolocation</td>
<td>14</td>
</tr>
</tbody>
</table>
The above table summarizes into the below table. Each parameter is also given by an interval rate, meaning the smallest scale in which the correspondent should be averaged if possible.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Greatness</th>
<th>Averaged Interval rate</th>
<th>Typical range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Marking age</td>
<td>(days) from application</td>
<td>days</td>
<td>Each 100 meters</td>
<td>0-2000</td>
</tr>
<tr>
<td>Thickness</td>
<td>At application</td>
<td>millimeters</td>
<td>Each 100 meters</td>
<td>0 - 5</td>
</tr>
<tr>
<td>Material</td>
<td>Type of material</td>
<td>(thermoplastic , sprayplastic (or paint))</td>
<td>Each 100 meters</td>
<td>1-3</td>
</tr>
<tr>
<td>Road type</td>
<td>Road type</td>
<td>Number of lanes, separated or not separated.</td>
<td>Each 100 meters</td>
<td></td>
</tr>
<tr>
<td>Road class</td>
<td>Policy</td>
<td>Class number</td>
<td>Each 100 meters</td>
<td>0-X</td>
</tr>
<tr>
<td>Profile</td>
<td>Structured or flat marking</td>
<td>Yes or No</td>
<td>Each 100 meters</td>
<td>0-1</td>
</tr>
<tr>
<td>P-class</td>
<td>From the Nordic certification system¹</td>
<td>Class</td>
<td>Each 100 meters</td>
<td>1-7</td>
</tr>
<tr>
<td>Linetype</td>
<td>Edge line, lane line or center line</td>
<td>Edge line, lane line or center line</td>
<td>Each 100 meters</td>
<td>1-4</td>
</tr>
<tr>
<td>Salting</td>
<td>Yes or No</td>
<td>Yes or No</td>
<td>Each 100 meters</td>
<td>0-1</td>
</tr>
<tr>
<td>Plowing</td>
<td>Yes or No</td>
<td>Yes or No</td>
<td>Each 100 meters</td>
<td>0-1</td>
</tr>
<tr>
<td>Curvature</td>
<td>radius</td>
<td>r/1000</td>
<td>Each 100 meters</td>
<td></td>
</tr>
<tr>
<td>Contractor</td>
<td>Will not be used</td>
<td>Will not be used</td>
<td>Each 100 meters</td>
<td></td>
</tr>
<tr>
<td>AADT</td>
<td>Average traffic intensity per day, year average</td>
<td>Vehicles per day</td>
<td>Each 100 meters</td>
<td></td>
</tr>
</tbody>
</table>

Data – format and apprehension

¹ Reference European Norm EN 1824
Data must be supplied for both response variables and the explanatory variables for the same sections and for a timespan that opens up for statistical analysis. A major discussion, which will not be part of this report, is how to standardize apprehending data from databases as this change from country to country.

For initial phases, the data must be gathered with a lot of manual work and will take a significant amount of time to apprehend, as the data-amount will be large. With time, it is therefore a key factor to see that data harvesting will be automatically apprehended and databases updated for future use.

Datatypes can be divided into three different types:

- **Administrative** (information from the specific road authority) – for example AADT, road-type, length, etc.
- **Material** - information from production – road authority or entrepreneurial
- **Functional** description – information from measurement of functional capabilities

All three datatypes must be provided. The administrative and material description is the explanatory variables, and the functional ones the response variables that will be used as the true values for developing the model and to calculate future development against a known functional status today.

The data to be supplied into the model should be on a scale that enables for justified analysis for its purpose. A model should be used to predict bigger areas for how road marking will develop and be maintained. This should also reflect in the data that will be put into the model. Therefore, it is suggested that data to be put into any analysis should be on an object-size approach. This is illustrated in the figure below. Every unique object should be chosen with homogeneity with respect to the explanatory variables (for example AADT, type of material, line type etc.). The response variables are averaged for the unique object. This is the smallest scale in which analysis are made upon. One suggestion is to beforehand see to that the road network gets divided into homogenous sections, with respect to some of the explanatory variables. As measurements arrive for a specific section – data analysis will be performed.
Figure 2, example of one acceptable two-lane road section for evaluation
Database

A first database where constructed for Denmark, Norway and Sweden gathering functional and descriptive data of road markings. For all countries it was managed to road marking data from ages zero to five years, which can be stated as enough in order to cover the life expectancy for road markings, see Figure 1, probability models for thermoplastic (left) and sprayplastic (right)

A database is constructed, which is inherited by the different parameters defined in chapter 4. The database is constructed by summarizing previous mobile controls of road marking functionality on standard measurement plans. In Sweden, that means delivery control year 0, and warranty control year two (possibly also year one). The database is then updated with new measurements on the correspondant sections in year three, four and five. After this period, it is likely safe to say that any marking will be worn out. Analysis are not based on the fact that analysis is made upon differences in between the same intervals, it is based upon trying to predict the correspondant level at level of age reached when these measurements where done. That also means that any arbitrary object in database can contain any arbitrary measurement date. The key becomes gathering enough data, and enough variance in the explanatory variables to be able to predict any arbitrary object in future reference. The Swedish and Norwegian functional dataset consists mainly of follow-up measurements on delivery and warranty controls, while the Danish is mostly data from measurement program in Stribeman.

<table>
<thead>
<tr>
<th>Country</th>
<th>No of 100-m intervals</th>
<th>Years</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sweden</td>
<td>39181</td>
<td>2013-2018</td>
<td>R_L, R_W, Q_D, SRT, C*</td>
</tr>
<tr>
<td>Norway</td>
<td>54034</td>
<td>2014-2018</td>
<td>R_L, R_W, Q_D, SRT, C*</td>
</tr>
<tr>
<td>Denmark</td>
<td>13788</td>
<td>2013-2018</td>
<td>R_L, R_W, Q_D, SRT, C*</td>
</tr>
</tbody>
</table>

*At present time data amount and interval years too small for analysis

After a thorough search of database material, the following parameters where managed to get hold of for the respective road owner in Sweden, Denmark and Norway. In Sweden, the main data source has been the Swedish National Road Database (or NVDB), in Norway it has been Vejkart.no and in Denmark Vejman.dk and Stribeman.dk. Some
Table 8. Apprehendable explanatory variables (F)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Sweden</th>
<th>Denmark</th>
<th>Norway</th>
</tr>
</thead>
<tbody>
<tr>
<td>Marking age</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Thickness</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Material</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Road type</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Road class</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Profile</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>P-class</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Linetype</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Salting</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Plowing</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Curvature</td>
<td>X</td>
<td>-</td>
<td>X</td>
</tr>
<tr>
<td>Contractor</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>AADT</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Coordinates</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Amount studded tires</td>
<td>X</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Model validation

Now we know how the model looks like and what the model should be inhabited with. The next steps are to see how one will work with developing the model, how calibrating it will work, how to validate and of course also how to update as new data arrives.

The basic concepts of model verification and validation are described in for example Thacker et al (2004) and give some philosophies in how to address a model program for verification and validation (also called V & V model program).
Machine learning model

As road marking deterioration is likely not a linear phenomenon and depends on a multiset of background parameters - which are both discrete and continuous, there will also be a demand for non-linear models. As data-amount will also be of a great scale and defined by that circumstances change over time – a machine learning approach can be adopted to make sure that the system accuracy is secured over time. The definition of machine learning is to learn from experience. Machine learning algorithms does not rely on a predetermined equation as the base of a model, but do rather adapt and improve performance as the number of samples available increase. Machine learning is already used vastly in forecasting scenarios and predicting maintenance.

Machine learning is defined by two ultimately different paths. Unsupervised or supervised learning. The unsupervised approach means that training is conducted without output data known to the user. Hence, clusters of the dataset will be analysed to find patterns. The supervised approach means that models are trained to a specific output data. In the RMMS case, the output data is already known – as
it is the response parameters defined. Input data is also known – the explanatory variables defined. Hence, supervised learning will be done (The MathWorks Inc 2016).

In supervised learning, models can be done either by regression or classification. Regression models try to functionalize input variables to numerical or continuous output variables. Regression fits predictions that will be in quantities or sizes. Classification fits functions aimed to discrete or categorical data that leads to one conclusion, for example: will housing prices likely go up or down?

In the RMMS case, regression models will likely be the best suitable. Amongst regression models, a series of different approaches are possible dependant on the nature of what to predict. In this work, the *MatLab regression learner* has been used in order to import data used in the RMMS project, select response parameters and explanatory variables in order to construct different scenarios of model outputs. Setup is made so that for every dataset, a series of different approaches for best fit is tested until the one with best fit and statistics will be chosen for training of new data.

From the module created, master curves for a series of different scenarios can be made, to fit into asset management systems that normally use linear functions to describe deterioration, classified by different scenarios. Such as dividing into type of road, material and position of the line.

Figure 2, machine learning process
**Step 1; Load from database**

The database implemented is made of a series of measurements of new and old road markings in Sweden, Norway and Denmark. The database is made up of mobile control of road marking made in ordinary road marking contracts, that are typically measured a couple of weeks after application, then again one or/and two years after. These measurements have been complemented with additional ones to gather data from the years three, four and five. Five years is a reasonable time to assume is the longest needed to gather the cycle of any road marking existing today.

Database placeholders has been future proofed by adding variables regardless of managing to apprehend them in relation to table 3.

**Step 2; Preprocessing of data**

To pre-process data, the following actions are taken:

- Measurement data from RMT system is calculated into 100-m intervals with GPS coordinates
- Measurement data is synced with explanatory variables. From databases from respective road owner, and from own created section summary database.
- Measurement data is labelled with a number and a letter (ID). The number is specific for the section. The letter is specific for the measurement instance. For example, number 1 and letter A means section number one, first time measurement. B means second time measurement and so on. This is so that sections can be easily compared using only identification, distance and line type.
- Measurement data that shows a positive development with more that 20% per year since last measurement are tossed, as an indicator on re-painting.

**Step 3; Define explanatory and response parameters**

In MatLAB, explanatory variables and response parameters are defined.

Response parameters are set to the functional road marking variables: RL(d), RL(w), Qd and SRT.

**Step 4; Train multiple models and validate**

It is now time to let the machine model try to fit a function or decision tree in order to guess road marking response parameters, using only the explanatory variables.

**Step 5; Select best fit**

The best fit function is described as the one with the least RMSE (root mean square error), and which has got a well-balanced residual plot.

**Step 6; Implement**

The function which has the best fit is packaged into a module. Here, it will be divided into clusters as describing functionality in practical terms. So that it can be implemented in an asset management system (where assets are commonly grouped, and each asset has its own deterioration curve.)
Step 7; train with new data
The function which has the best fit is packaged into a module, where it can be retrained with any new dataset, at any time.

Regression

Regression of database where conducted with Excels built in program Regression analysis toolpak, to point significant factors for describing road marking deterioration. As seen below, the majority of explanatory variables have significant impact to the model.

**Retroreflection dry \( R_{L,d} \)**

Adjusted R2 was in the magnitude of 0.4 for RL(dry). Number of observations \( N= 107003 \).

**Retroreflection wet \( R_{L,w} \)**

Adjusted R2 was in the magnitude of 0.47 for RL(wet). Number of observations \( N= 28531 \).

**Daytime luminance \( Q_D \)**

Adjusted R2 was in the magnitude of 0.38 for QD. Number of observations \( N= 79950 \).

**Skid resistance \( SRT \)**

Adjusted R2 was in the magnitude of 0.26 for SRT Number of observations \( N= 78337 \).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>RL (dry) ( P &lt; 0.05 ? )</th>
<th>RL(wet) ( P &lt; 0.05 ? )</th>
<th>QD ( P &lt; 0.05 ? )</th>
<th>SRT ( P &lt; 0.05 ? )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Marking age</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Thickness</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Material</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Road type</td>
<td></td>
<td>Yes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Road class</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Profile</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>P-class</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Linetype</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Salting</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Plowing</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Curvature</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Contractor</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>-------------</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td></td>
</tr>
<tr>
<td>AADT</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Amount studded tires</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
</tbody>
</table>
Machine learning results

Sweden

Below the results from the machine learning model is outputted. The machine model where constructed upon 75% of the database, whereas 25% of the data where held out for validation. Validated data output is showed below.

Output of RL(dry) showed an $R^2$ of 0.7 and a root mean square error (RMSE) of 31.5, whereas output from SRT showed showed an $R^2$ of 0.78 and a root mean square error (RMSE) of 2.2. Output from Qd showed a $R^2$ of 0.78 and a root mean square error (RMSE) of 10.04. Output from RL(wet) showed a $R^2$ of 0.71 and a root mean square error (RMSE) of 5.2.

Figure 3, relationship between predicted and true response of RL(d), RL(w), Qd and SRT.
Norway

Below the results from the machine learning model is outputted. The machine model where con-
structed upon 75% of the database, whereas 25% of the data were held out for validation. Validated
data output is shown below.

Output of RL(dry) showed an R2 of 0.64 and a root mean square error (RMSE) of 36.8, whereas out-
put from SRT showed an R2 of 0.85 and a root mean square error (RMSE) of 2.0. Output from Qd showed a R2 of 0.79 and a root mean square error (RMSE) of 10.8. Output from RL(wet) showed a R2 of 0.68 and a root mean square error (RMSE) of 7.5.

Figure 4, relationship between predicted and true response of RL(d), RL(w), Qd and SRT.
Denmark

Below the results from the machine learning model is outputted. The machine model where constructed upon 75% of the database, whereas 25% of the data where held out for validation. Validated data output is showed below. Only $R_{L,D}$ was modelled as the amount of data for other functional parameters where too low at present time.

Output of RL(dry) showed an R2 of 0.52 and a root mean square error (RMSE) of 48.3.

Figure 4, relationship between predicted and true response of RL(d)
Previous models to validate

The work conducted by Lundkvist (2014) proposed the below models that showed good correlation. These models were tested against the Swedish database, where RL(dry) where the predictor and road type and if the marking is profiled or not were implemented.

Table 10, model for evaluation of RL(dry)

<table>
<thead>
<tr>
<th>Road Type</th>
<th>Profiled (Y/N)</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>HW</td>
<td>N</td>
<td>RL=260-31*YEAR</td>
</tr>
<tr>
<td></td>
<td>Y</td>
<td>RL=332-46*YEAR</td>
</tr>
<tr>
<td>2+1 type road (sep.)</td>
<td>N</td>
<td>RL=255-27*YEAR</td>
</tr>
<tr>
<td></td>
<td>Y</td>
<td>RL=333-41*YEAR</td>
</tr>
<tr>
<td>2-lane road (not sep.)</td>
<td>N</td>
<td>RL=243-27*YEAR</td>
</tr>
<tr>
<td></td>
<td>Y</td>
<td>RL=267-41*YEAR</td>
</tr>
</tbody>
</table>

The results were non-significant when adopting these rules to the dataset. One explanation could be that the model above was made in a different scaling than the RMMS database, where the RMMS database consists of 100 meter segments, whereas the above models were made for homogeneous objects. This could be tested in further work.
Summary

The scope of this report was to test the hypothesis that road marking functional parameters can be derived from a series of explanatory variables. Work in this report can conclude that the hypothesis has been proven with a statistically significant result. Explanatory variables in this report concluded that models can be built with machine learning models in order to be retrained as new data comes in. Models made has a coefficient of determination of between 0.4 to 0.7 and standard deviations span from 10-20%. This suggests that a significant correlation has been found that could be used in order to predict road marking functionality in asset management planning. It also suggests that such models could get better by training with new data, testing of new explanatory variables not tested in this report or testing of other models in order to explain the dependant factors. A general conclusion is also that it seems applicable to use a machine-learning approach in order to explain road marking deterioration – which is not a linear phenomena. Road owners is therefore recommended to keep a database with at least the placeholders in this report, and also to adopt machine models when estimating road marking performance. Deterioration in asset management system is normally categorized and then expected to be a linear phenomena. Master curves could be used from machine models in order to make those categorizations and make possible to add linear functions.

For retroreflection dry, the number of individual datapoints where sufficient for analysis of all participating countries. For Sweden and Norway, also for wet retroreflection, daytime luminance and friction. In Denmark, this data came from the project called ROMA, and data gathered so far in that project is not sufficient yet for analysis, but will likely be in a few years time. Although it is not necessary that the use of deterioration models for anything else than retroreflection dry is necessary, as this factor stands for the absolute majority of the disapproved cases – hence this parameter tends to be the first one to fail in all cases.

In further work, it is recommended that systematic gathering of explanatory and descriptive data in this study is implemented in the respective countries asset management strategy. It has been proven quite hard to find road marking material specific data. Thickness, which ought to be one very important factor, is not gathered in a way that can be traced to a specific coordinate. Plowing and salting, which is also a significant factor, should also be targeted.

The work here is to be considered as a first step. It has been proven that machine learning models can be used in order to with a statistical certainty describe functional development of road markings over time. If databases can be constructed as in this document, and the machine model adopted in this work can be implemented – models can continue to improve over time. As road markings are a living material and are not constant over time, model work will never be completed but always evolve. That is why keeping databases up to date on a yearly basis, complemented by road marking performance data, is a key factor in success of using deterioration models for predicting future maintenance and budget needs.
References


—. "Road Marking Management System." Linköping, 2015.

Appendices

Appendice

Appendice A, MatLAB code example

Import file

function Databas100m = importfile(workbookFile, sheetName, startRow, endRow)
  %IMPORTFILE Import data from a spreadsheet
  % DATABAS100M = IMPORTFILE(FILE) reads data from the first worksheet in
  % the Microsoft Excel spreadsheet file named FILE. Returns the data as
  % a table.
  %
  % DATABAS100M = IMPORTFILE(FILE, SHEET) reads from the specified
  % worksheet.
  %
  % DATABAS100M = IMPORTFILE(FILE, SHEET, STARTROW, ENDROW) reads from
  % the specified worksheet for the specified row interval(s). Specify
  % STARTROW and ENDROW as a pair of scalars or vectors of matching size
  % for dis-contiguous row intervals.
  %
  % Example:
  % Databas100m = importfile("K:\Uppdrag\CN\NordFoU - RMMS 1320023349\2_AR-BETSM\2_XLS_M\Databas\Databas_100m.xlsm", "DB_100m", 2, 52083);
  %
  % See also READTABLE.
  %
  % Auto-generated by MATLAB on 25-Jan-2019 10:03:07

  % Input handling
  %
  % If no sheet is specified, read first sheet
  if nargin == 1 || isempty(sheetName)
    sheetName = 1;
  end

  % If row start and end points are not specified, define defaults
  if nargin <= 3
    startRow = 2;
    endRow = 52083;
end

%% Setup the Import Options
opts = spreadsheetImportOptions("NumVariables", 98);

% Specify sheet and range
opts.Sheet = sheetName;
opts.DataRange = "A" + startRow(1) + ":CT" + endRow(1);

% Specify column names and types


opts = setvaropts(opts, [3, 16, 18, 21, 29, 30, 44, 47, 49, 50, 51, 52, 53, 54, 55, 56, 57, 59, 60, 62, 63, 64, 65, 68, 69, 70, 71, 72, 73, 82, 92, 98], "WhitespaceRule", "preserve");
opts = setvaropts(opts, [1, 2, 3, 4, 5, 7, 16, 18, 21, 29, 30, 44, 47, 49, 50, 51, 52, 53, 54, 55, 56, 57, 59, 60, 61, 62, 63, 64, 65, 68, 69, 70, 71, 72, 73, 80, 82, 83, 87, 88, 92, 96, 97, 98], "EmptyFieldRule", "auto");

% Import the data
Databas100m = readtable(workbookFile, opts, "UseExcel", false);

for idx = 2: length(startRow)
    opts.DataRange = "A" + startRow(idx) + ":CT" + endRow(idx);
    tb = readtable(workbookFile, opts, "UseExcel", false);
    Databas100m = [Databas100m; tb]; %#ok<AGROW>
end
end

Train model

function [trainedModel, validationRMSE] = trainRegressionModel(trainingData)
% [trainedModel, validationRMSE] = trainRegressionModel(trainingData)
% returns a trained regression model and its RMSE. This code recreates the
% model trained in Regression Learner app. Use the generated code to
% automate training the same model with new data, or to learn how to
% programmatically train models.
% % Input:
% %       trainingData: a table containing the same predictor and response
% %       columns as imported into the app.
% % % Output:
% %       trainedModel: a struct containing the trained regression model. The
% %       struct contains various fields with information about the trained
% %       model.
% %       trainedModel.predictFcn: a function to make predictions on new data.
% %       validationRMSE: a double containing the RMSE. In the app, the
% %       History list displays the RMSE for each model.
% % Use the code to train the model with new data. To retrain your model,
% % call the function from the command line with your original data or new
% % data as the input argument trainingData.
% % For example, to retrain a regression model trained with the original data
% % set T, enter:
% %   [trainedModel, validationRMSE] = trainRegressionModel(T)
% To make predictions with the returned 'trainedModel' on new data T2, use
% yfit = trainedModel.predictFcn(T2)
%
% T2 must be a table containing at least the same predictor columns as used
% during training. For details, enter:
% trainedModel.HowToPredict

% Extract predictors and response
% This code processes the data into the right shape for training the
% model.
inputTable = trainingData;
predictorNames = {'Country', 'Region', 'Road', 'GPSXfrom', 'GPSYfrom', 'GPSXto', 'GPSYto', 'Material', 'Applied', 'AADT', 'Lanewidth', 'Roadclassification', 'Linetype', 'Salting10', 'Plowing10', 'Amountstuddedtires', 'Roadwidthm', 'DOM', 'NyB', 'Sl', 'Pro', 'RBr', 'DTfordon', 'Beltyp'};
predictors = inputTable(:, predictorNames);
response = inputTable.RLt;
isCategoricalPredictor = [true, true, false, false, false, false, false, false, false, false, false, false, false, false, false, true, true, true, false, true, false, true, false, true];

% Train a regression model
% This code specifies all the model options and trains the model.
regressionTree = fitrtree(...
    predictors, ...
    response, ...
    'MinLeafSize', 12, ...
    'Surrogate', 'off');

% Create the result struct with predict function
predictorExtractionFcn = @(t) t(:, predictorNames);
treePredictFcn = @(x) predict(regressionTree, x);
trainedModel.predictFcn = @(x) treePredictFcn(predictorExtractionFcn(x));

% Add additional fields to the result struct
trainedModel.RequiredVariables = {'Country', 'Region', 'Road', 'GPSXfrom', 'GPSYfrom', 'GPSXto', 'GPSYto', 'Material', 'Applied', 'AADT', 'Lanewidth', 'Roadclassification', 'Linetype', 'Salting10', 'Plowing10', 'Amountstuddedtires', 'Roadwidthm', 'DOM', 'NyB', 'Sl', 'Pro', 'RBr', 'DTfordon', 'Beltyp'};
trainedModel.RegressionTree = regressionTree;
trainedModel.About = 'This struct is a trained model exported from Regression Learner R2018b.';
trainedModel.HowToPredict = sprintf('
To make predictions on a new table, T, use:
\n yfit = c.predictFcn(T) \nreplacing ''c'' with the name of the variable that is this struct, e.g. ''trainedModel''. \n\nThe table, T, must contain the variables returned by: \n c.RequiredVariables \nVariable formats (e.g. matrix/vector, datatype) must match the original training data. \nAdditional variables are ignored. \nFor more information, see <a href="matlab:helpview(fullfile(docroot, ''stats'', ''stats.map''), ''apgression_exportmodeltoworkspace'">How to predict using an exported model</a>.');

% Extract predictors and response
% This code processes the data into the right shape for training the model.
inputTable = trainingData;
predictorNames = {'Country', 'Region', 'Road', 'GPSXfrom', 'GPSYfrom', 'GPSXto', 'GPSYto', 'Material', 'Applied', 'AADT', 'Lanewidth', 'Roadclassification', 'Limetype', 'Salting10', 'Plowing10', 'Amountstuddedtires', 'Roadwidthtm', 'DOM', 'NyB', 'Sl', 'Pro', 'RBr', 'DTfordon', 'Beltyp'};
predictors = inputTable(:, predictorNames);
response = inputTable.RLt;
isCategoricalPredictor = [true, true, false, false, false, false, false, false, false, false, false, false, true, true, false, true, false, true, false, true, false, true];

% Set up holdout validation
cvp = cvpartition(size(response, 1), 'Holdout', 0.25);
trainingPredictors = predictors(cvp.training, :);
trainingResponse = response(cvp.training, :);
trainingIsCategoricalPredictor = isCategoricalPredictor;

% Train a regression model
% This code specifies all the model options and trains the model.
regressionTree = fitrtree(...
    trainingPredictors, ...
    trainingResponse, ...
    'MinLeafSize', 12, ...
    'Surrogate', 'off');

% Create the result struct with predict function
treePredictFcn = @(x) predict(regressionTree, x);
validationPredictFcn = @(x) treePredictFcn(x);
% Add additional fields to the result struct

% Compute validation predictions
validationPredictors = predictors(cvp.test, :);
validationResponse = response(cvp.test, :);
validationPredictions = validationPredictFcn(validationPredictors);

% Compute validation RMSE
isNotMissing = ~isnan(validationPredictions) & ~isnan(validationResponse);
validationRMSE = sqrt(nansum((validationPredictions - validationResponse).^2)) / numel(validationResponse(isNotMissing));

Appendix B, Database structure

Database placeholders are:

ID
Unique ID for one section of road. This section have been measured a multiple of times (the multiple explained as a variable letter. For example 1A is unique object one, measured the first time, B is the second time etc

Code
Filename of the file when it was measured. Can be anything but makes file traceable.

Country
Origin of the measurement

Region
Specific region, as defined by state Agency

Road
Specific road number

Section
A defined start and end point of a particular ID. Given in NVDB for Sweden, HP in Norway and km in Denmark

Length
The difference in length between the section start and stop, in meters

GPS X from
Coordinate given in WGS 84, start X

GPS Y from
Coordinate given in WGS 84, start Y

GPS X to
Coordinate given in WGS 84, stop X

GPS Y to
Coordinate given in WGS 84, stop Y

Contractor
Performer of roadmarking on the specific section
Material
Type of material; thermoplastic, spray or paint

Applied
Date of road marking application (YYYY-DD-MM)

Thickness (mm)
At application

Profile
Statement if road marking is profiled (Type II) or not profiled (Type I)

P-class
P-class from Nordic certification system

AADT
Mean yearly traffic intensity per day (vehicles per day)

Lane width
Total lane width (distance between edge lines)

Climate
Climate class

Road classification
Highway (4-lane of higher), 2+1 road (three lanes), two lane road or one lane road

Speed limit
Speed limit in km/h

Linetype
Right edge line, left edge line, center line or lane line.

Salting
If section is salted during the winter period or not

Plowing 1/0
If section is salted during the winter period or not

Curvature
Curvature of road

Amount studded tires
The amount of studded tires, in percent for the section

DOM
Measurement date (YYYY-MM-DD)

RL(d)
Retro-reflection in dry conditions (mcd/(m²*lux))

RL(w)
Retro-reflection in wet conditions (mcd/(m²*lux))

Qd
Daytime visibility (mcd/(m²*lux))

SRT
Friction in SRT units

C
Road marking coverage in percent
Appendice C, interval amount matrix

<table>
<thead>
<tr>
<th>Country</th>
<th>Total amount intervals</th>
<th>Regions included</th>
<th>Counties included</th>
<th>Intervals $R_{LD}$</th>
<th>Intervals $R_{LW}$</th>
<th>Intervals $Q_{D}$</th>
<th>Intervals SRT</th>
</tr>
</thead>
<tbody>
<tr>
<td>SE</td>
<td>39181</td>
<td>4</td>
<td>6</td>
<td>39181</td>
<td>5185</td>
<td>27991</td>
<td>27200</td>
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<tr>
<td>DK</td>
<td>13788</td>
<td>3</td>
<td>19</td>
<td>13788</td>
<td>420*</td>
<td>835*</td>
<td>821*</td>
</tr>
<tr>
<td>NO</td>
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<td>1</td>
<td>7</td>
<td>54034</td>
<td>23346</td>
<td>51959</td>
<td>51137</td>
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</tbody>
</table>

*Not included in analysis