Impact of Cold Climate on Failures in Railway Infrastructure

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Abstract—
Railway traffic has increased over the last decade due to greater energy costs and the need to reduce emissions. Ensuring the dependability and capacity of railway infrastructure requires efficient and effective maintenance which, in turn, requires good understanding of various physical behaviours, e.g. deterioration and environmental effects. This paper studies the effect of cold climate on railway infrastructure performance using statistics and historical work order data. It finds differences in the number of work orders as a function of season and geographical location.

Keywords— railway, performance, temperature, winter, cold, climate, failures, infrastructure, snow, ice, maintenance, reliability, dependability

I. INTRODUCTION
Railway traffic has increased over the last decade and is likely to increase further with the shifting of passengers and cargo from road to rail, due to increasing energy costs and the demand to reduce emissions (EC 2010, EC 2011). For example, the goals of the 2011 White Paper for the European transport system include a 50 % shift of medium distance intercity passenger and freight journeys from road to rail and water, and a 60 % cut in transport CO₂ emissions by 2050 (EC 2011). Meeting these demands requires increased dependability and capacity of railways which, in turn, requires efficient and effective maintenance. By understanding the deterioration processes of railway infrastructure and how they are linked to the effects of both operation and the environment, a railway company can plan its maintenance in a more proactive way, e.g. corrective and preventive maintenance can be optimised.

A cold climate is known to have an effect on railway infrastructure and its components. In Sweden, the winters were particularly harsh in 1965-66 (SJ 1966), 2001-02 (Banverket 2002), 2006-07 (VTI 2007), 2009-10 and 2010-11 (Unckel 2010, UIC 2011a, UIC 2011b)

Scientific publications on a cold climate and railways are sparse. In a survey carried out by the International Union of Railways (UIC), 11 European countries said their main winter rolling stock challenges stemmed from: train design (58 %) and infrastructure (34 %). Seventeen responses cited the main winter challenges in the infrastructure as: performance of equipment for snow clearance (29 %), switches and crossings (27 %) and rails and welding (20 %). VTI (Swedish National Road and Transport Research Institute) studied data from two Swedish railway sections in the period 2001-03 and found that the number of failures causing train delays was 41 % higher in winter than in summer (VTI 2007). The increase was 130 % in switches and crossings, and 24 % in the other railway infrastructure systems. Winter was considered as starting 1 October and ending 30 April, i.e. 58 % of the year.

In this study, after examining the various issues of a cold climate and its effect on a railway’s infrastructure failures, we analyse data collected by a Swedish railway company over several years. Sweden is chosen as a case study for two reasons. For one thing, Sweden is known to have harsh winters. For another, since Sweden is an oblong country, stretching about 1500 km from north to south, it is possible to study geographical effects while working with data from only one infrastructure manager (IM), in this case, Trafikverket (Swedish Transport Administration).

The study considers two main research questions:
- Can winter and summer failure dependencies be found by studying historical failure data of railway infrastructure?
- Can differences in failures of railway infrastructure due to seasonal effects between northern and southern Sweden be found by studying historical failure data?

II. COLD CLIMATE AND FAILURES
A railway system integrates a number of systems and maintainable components; it comprises a variety of materials and many complex functional configurations, which extend from one geographical location to another. The subsystems range from simple electronic signal systems, such as balise, to large power systems, such as catenary, as well as track structures, such as turnouts and tunnels.

The reasons for infrastructure failure and traffic interruption are not limited to the inherent capability of the system, the operational profile or maintenance practices. The environmental effect on asset performance and failure characteristics must also be considered, especially in a cold climate.
The impact of cold climatic conditions depends on the type of asset. In fact, a major factor to consider is the effect of temperature on different materials. All carbon steels undergo a ductile-to-brittle transition, which reduces the impact toughness as the temperature is lowered (Roe et al. 1990, Siewert et al. 2000). The point of transition and the reduction in impact toughness, which can be reduced to one tenth, depend on the chemical composition of the asset, the product processing and the service environment. A similar phenomenon, the glass transition temperature, occurs in amorphous materials, polymers and glasses (Zarzycki 1991, ISO 1999). Below the glass transition temperature, amorphous materials become stiffer and more brittle due to their molecularly locked state. Well known problems caused by temperature transitions include ship failures during World War II (Roe et al. 1990, Siewert et al. 2000) and the Space Shuttle Challenger accident in 1986 (Rogers Commission 1986).

In rolling stock, a cold climate has been shown to increase wheel wear and damage, e.g. (Palo et al. 2012).

Low temperatures are also believed to impact track structures; specifically, changes in the material properties of the components lead to increased degradation rate. The local stiffness of the steel rail is not significantly affected by low temperatures, but global stiffness is believed to be affected by ground frost in the ballast and substructure. In addition, the fracture toughness of steel components changes with temperature and contributes to the propensity for failure.

III. ANALYSIS OF FAILURE DATA

For the study, we collect, verify and analyse operation and maintenance data for two Swedish railway lines: Kiruna, line 21, and Växjö, line 4. Växjö is located between Göteborg and Kalmar. The linear distance between Växjö and Kiruna is about 1200 km. Line 21 is a 400 km 30 tonne mixed traffic heavy haul line stretching from Riksgränsen to Boden; Line 4 is a 350 km mixed traffic line running from Göteborg to Kalmar, see Fig. 1.

The data from Trafikverket constitute work orders (WOs) for corrective maintenance. Corrective maintenance data consist of urgent inspection remarks reported by the maintenance contractor, as well as failure events and failure symptoms identified outside the inspections, commonly reported by the train driver, but occasionally reported by the public. The work orders’ failure reports include the three categories of RAM (reliability, availability and maintainability) failure as identified by the European Standards 50126 (CEN 1999), see Fig. 2. Failures identified outside inspections include the following (Banverket 2010):

- Accidents with animals
- Inspections after wheel impact
- Actions after failure in railway safety equipment
- Actions after alarms
- Actions after report from operators or others
- Actions after suspecting failure
- Lowering failed pantographs

Immediate action is required if the fault negatively influences the following (Trafikverket 2010):

- Safety
- Train delays
- Third parties
- Environment

Temperature data are supplied by SMHI (Swedish Meteorological and Hydrological Institute) for both lines.

Fig. 1 Map of Sweden showing railway lines 21 and 4

The data span over 11 years, from 2001 to 2012. Lines 21 and 4 consist of 25678 WOs and 15772 WOs, respectively.

IV. RESULTS AND DISCUSSION

In what follows, we divide the results, with the accompanying discussion, into six sections:

- Seasonal temperature; summer/winter and north/south
- Work orders over time; from 2001 to 2012
- Work order per month; mean over 11 years
- Analysis of variance; study of significance
- Mean temperature and failures; monthly mean versus monthly number of work orders
- Analysis after discounting snow and ice failures

**A. Seasonal temperature**

When we plot the monthly mean temperature of Kiruna and Växjö, we see that the northern part of Sweden has a more extreme temperature range. The standard deviation of the temperature is 7.0 for Växjö and 9.2 for Kiruna (Fig. 3). A larger temperature range between summer and winter might result in more failures as the probability of crossing temperature transition domains is higher.

![Monthly mean temperature of Kiruna and Växjö](image)

**Fig. 3 Monthly mean temperature of Kiruna and Växjö, based on data from 2001-2012**

**B. Work orders over time**

A simple way to study seasonal effects is to plot the number of work orders over time (Fig. 4). The winter problems on line 21 in 2006-07, as reported by (VTI 2007), and in 2009-10 and 2010-11 by (Unckel 2010, UIC 2011a, UIC 2011b, Linné et al. 2012), are shown in Fig. 4 and are highlighted by the two circles. The extreme conditions of the latter two periods correspond to the peaks marked by a single circle for line 4 in the lower part of the figure.

Interestingly, the winter of 2001-02, as reported by (Banverket 2002), does not have a similarly sharp peak for either line, perhaps due to the quality of data or the reporting system. In 2007-08, a new passing siding was introduced on line 21, Tolikberget, giving a high number of failures in the first months of 2008. A new section was opened in 2010 to the Aitik copper mine; this resulted in about eight work orders in 2010. It should, therefore, not affect the peaks in Fig. 4 markedly.

The figure shows that the ratio of the maximum and minimum number of work orders is about two, implying a large variation in monthly work orders over the years.

![Number of work orders (WOs) from 2001 to 2012](image)

**Fig. 4 Number of work orders (WOs) from 2001 to 2012**

**C. Work orders per month**

In the next figure, Fig. 5, the 11 years of work orders have been put into periods of seven days and divided by 11; i.e. each month consists of four bars, with each bar giving the seven day mean, based on 11 years of data. The final days in months longer than 28 days are not considered. For line 21, the number of work orders in the spring and autumn is half the number in January/February at the peak of the winter. This effect is not as clear for line 4, arguably because there is less precipitation in the south. The effect of precipitation is studied in later sections of the paper.

![Number of work orders (WOs) per 7 days. 11 year mean](image)

**Fig. 5 Number of work orders (WOs) per 7 days. 11 year mean**

A critical system in terms of capacity impact and maintenance cost is the switches and crossings (S&C) system. Innotrack IMs ranked S&C as the third most problematic system in terms of cost impact, after track geometry and rail failures (INNOTRACK 2010). It is interesting, therefore, to
analyse the work orders on this system, see Fig. 6. A comparison of winter and summer shows two to five times more work orders in winter. Using regression analysis, in this case 6th order polynomial model, the difference is about two to three times. $R^2$ is 0.81 and 0.65 for lines 21 and 4, respectively. $R^2$ increases with fewer bars, e.g. the monthly mean for line 21 gives a $R^2$ of 0.93.

![Fig. 6 Number of work orders (WOs) on switches and crossings per 7 days. 11 year mean](image1)

![Fig. 7 Seasonal effects on the number of work orders per day on Lines 21 and 4](image2)

### D. Analysis of variance

The previous section shows winter dependency. As this represents a subjective inference, this section investigates the phenomenon by analysing variance.

More specifically, it analyses the difference in the work orders in the calendar months over the 11 year period of investigation to establish whether the observed difference is by chance and if it is statistically significant. Previous sections of the paper show that there are variations in the number of work orders in the years considered and in the months of the year. Fig. 7 distinctly shows that the average work order per day differs for each month. For line 21, the average number of daily work orders for the period of time under investigation is about six. However, the average daily work orders of some months are higher than the overall average, while other months are lower. Similarly, the average number of daily work orders for line 4 is about four, possibly separating the year into high and low daily work order periods.

The quasi-sinusoidal curves in Fig. 7 likely show the influence of the cold climate on failures in railway infrastructure. To further investigate the observed seasonal changes in the number of work orders, we divide the annual time horizon into four seasons, each consisting of two months. The months selected for summer are June and July, autumn includes September and October, winter comprises January and February and spring is April and May.

The individual value plot from Minitab (Montgomery 2009) in Fig. 8, shows the average number of daily work orders in the different seasons. For line 21, the average number of daily work orders is higher in winter than other seasons and also more spread out. The average number of daily work orders in summer over the years 2001 to 2011 is higher than the overall average for all eight months (about six work orders). The daily work orders in the spring and autumn appear to be similar and the averages are markedly below the overall average. For line 4, the number of daily work orders in the different seasons appears to be more consistent; nonetheless, the mean of the number of work orders is highest in winter and lowest in spring.
The difference in the volume of work orders in the various seasons could be due to any of a number of reasons, including chance, operation profile, condition of rolling stock, maintenance philosophy or strategy, and the trustworthiness of the findings should be tested. Testing the equality of the mean daily work orders for the four periods requires performing statistical inference using procedures such as t-test or analysis of variance (ANOVA). To avoid calculation complexities, pairwise comparison and type I error, we have used the ANOVA procedure, as it is the appropriate procedure for testing the equality of several means (Montgomery 2009).

Since season is the only independent factor being investigated, we deploy a one-way ANOVA model. The conditions for model adequacy are confirmed by using Minitab, i.e. randomness, normal distribution and equality of variance of the number of daily work order.

The result of the one-way ANOVA statistical inference is shown in Tables I and II. Table I shows that for line 21, the means of the daily work orders in the different seasons are not equal, as the p-value of the test is less than 0.05. This difference is statistically significant, with a significance level of 0.05. Winter has a significantly higher number of work orders than the other seasons. It cannot be established statistically that there is a significant difference between other periods from the results in Table I. It is important to point out that the observed greater number of work orders in the summer compared to both autumn and spring is a result of the maintenance philosophy and practice of the infrastructure manager. There is a high inspection frequency during this period. Urgent inspection remarks are always logged into the corrective maintenance data base, and work orders are launched.

**TABLE I**

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Season</td>
<td>3</td>
<td>99,2</td>
<td>33,1</td>
<td>13,6</td>
<td>0,000</td>
</tr>
<tr>
<td>Error</td>
<td>84</td>
<td>204,9</td>
<td>2,4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>87</td>
<td>304,2</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

S = 1,6   R-Sq = 32,6%   R-Sq(adj) = 30,2%

**Individual 95% CIs For Mean Based on Pooled StDev:**

<table>
<thead>
<tr>
<th>Level</th>
<th>N</th>
<th>Mean</th>
<th>StDev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Autumn</td>
<td>22</td>
<td>5,1</td>
<td>0,74</td>
</tr>
<tr>
<td>Spring</td>
<td>22</td>
<td>5,7</td>
<td>1,02</td>
</tr>
<tr>
<td>Summer</td>
<td>22</td>
<td>6,5</td>
<td>1,36</td>
</tr>
<tr>
<td>Winter</td>
<td>22</td>
<td>7,9</td>
<td>2,51</td>
</tr>
</tbody>
</table>

Pooled StDev = 1,56

DF = Degrees of freedom  F = F-ratio  SS = Sum of squares  P = p-value  MS = Mean square

Similarly, Table II shows that for line 4, the means for the daily work orders in the different seasons are not equal, as the p-value of the test is less than 0.05. There is a significant difference in the number of daily work orders for winter and spring and for winter and autumn, but there is no difference between winter and summer. The reason is likely the same as that given previously for line 21.

**TABLE II**

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Season</td>
<td>3</td>
<td>5,9</td>
<td>1,97</td>
<td>5,1</td>
<td>0,003</td>
</tr>
<tr>
<td>Error</td>
<td>84</td>
<td>32,8</td>
<td>0,39</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>87</td>
<td>38,7</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

S = 0,62   R-Sq = 15,3%   R-Sq(adj) = 12,3%

**Individual 95% CIs For Mean Based on Pooled StDev**

<table>
<thead>
<tr>
<th>Level</th>
<th>N</th>
<th>Mean</th>
<th>StDev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Autumn</td>
<td>22</td>
<td>3,61</td>
<td>0,52</td>
</tr>
<tr>
<td>Spring</td>
<td>22</td>
<td>3,55</td>
<td>0,67</td>
</tr>
<tr>
<td>Summer</td>
<td>22</td>
<td>3,96</td>
<td>0,49</td>
</tr>
<tr>
<td>Winter</td>
<td>22</td>
<td>4,19</td>
<td>0,78</td>
</tr>
</tbody>
</table>

Pooled StDev = 0,62

3,30  3,60  3,90  4,20
An interesting aspect of the ANOVA analysis is its ability to investigate the difference between the number of failures on line 21 in the colder northern part of Sweden (see Fig. 3) and line 4 in the southern part of the country.

Using the historical temperature data of two locations on lines 21 and 4 over the given years (displayed in Fig. 3) the winter period is redefined as the coldest months, i.e. December, January and February. The ratio of the number of failures in the three coldest months to the total number of failures in each year is estimated, and the results appear in Fig. 9. We can see that the percentage of winter work orders for line 21 is higher than for line 4.

![Individual Value Plot of % Winter work order](image)

Fig. 9: Percent of WOs that occurs in December, January and February on line 21 and 4.

To confirm the difference in the seasonal effects on failures between the lines, we carry out an ANOVA test; see Table III. The procedure shows that the degree of winter effect on the failure of the two lines is statistically different to a significant level of 0.05. In addition, within a 95% confidence interval, the degree of winter effect on failures between the lines does not overlap, showing distinction between the two lines. Line 21, where the cold climate is harsher, has a higher degree of winter effect on failures than line 4.

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Factor</td>
<td>1</td>
<td>68,5</td>
<td>68,5</td>
<td>9,95</td>
<td>0.005</td>
</tr>
<tr>
<td>Error</td>
<td>20</td>
<td>137,8</td>
<td>6,9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>21</td>
<td>206,3</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

S = 2,6  R-Sq = 33,2%  R-Sq(adj) = 29,9%

Individual 95% CIs For Mean Based on Pooled StDev:

<table>
<thead>
<tr>
<th>Level</th>
<th>N</th>
<th>Mean</th>
<th>StDev</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Line 4</td>
<td>11</td>
<td>26,456</td>
<td>2,019</td>
<td>(24,3, 28,6)</td>
</tr>
<tr>
<td>Line 21</td>
<td>11</td>
<td>29,986</td>
<td>3,114</td>
<td>(27,8, 32,1)</td>
</tr>
</tbody>
</table>

Pooled StDev = 2,62

Lastly, we examine consistency over the 11 year period; see Fig. 10. We divide the work orders of January and February by the work orders of April and May. The resulting standard deviation is quite large, making prediction difficult just by studying means over a long time.

In addition, the mean ratio is higher for line 21 in the north, possibly because there is more precipitation; another reason could be the bigger difference between winter and summer temperatures in the north, shown in Fig. 3.

![Ratio [WOs/WOs]](image)

Fig. 10 Winter to spring ratio of 2001-2011. Difference in number of days in months has been compensated.

### E. Mean temperature and failures

Previous sections examine seasonal dependency in the work orders, i.e. temperature and precipitation dependency; they also look at distribution and dispersion. This section studies the work orders as a function of the monthly mean temperature. When we examine all work orders for line 21, we see that the variation is very high, giving a bad fit (Fig. 11). The number of influencing parameters is especially high when all the subsystems of the railway infrastructure are considered. While the number of work orders seems to increase with the absolute temperature, this may be because there are more track inspections during the summer when the weather is pleasant, i.e. high temperature does not necessarily mean more failures.

![WOs per month](image)

Fig. 11 Work orders (WOs) and mean temperature per month of line 21. Gives a bad fit.
By carrying out a similar analysis for switches and crossings, we get a better, albeit still unsatisfactory, fit (Fig. 12).

**F. Analysis after discounting snow and ice failures**

Snow and ice seem to account for a large part of railway failures in cold climate. For the northern line 21, 2055 WOs of the 25678 WOs are due to snow and ice, i.e. 8 %. In this section, we analyse the remaining 23623 WOs for line 21.

When we examine the work orders per month (Fig. 13), we see that the peak in January is about 60 % higher than the lowest point, compared to about 100 % in Fig. 5. But the winter effect can still be seen; in this case, it should be mainly the effect of low temperatures, as snow and ice work orders are omitted.

Variations in seasonal dependency can be seen in Fig. 14, i.e. dispersion in winter to spring ratio. Compared to data that include snow and ice problems, i.e. Fig. 8, the mean ratio is reduced from 1.38 to 1.16.

Figs. 12-14 Switches and crossings work orders (WOs) and mean temperature per month. Data of 2001-2012

Finally, we consider mean temperature and failures for switches and crossings and find no temperature dependency (Fig. 16). The result concurs, therefore, with Fig. 15, i.e. winter effects in switches and crossings are mainly due to snow and ice.

**V. CONCLUSIONS**

Looking at the case of a railway in Sweden, the study finds that the cold Nordic climate has an impact on the dependability of railway infrastructure. This, in turn, affects the capacity and quality of service of the assets and increases...
the volume of maintenance work. A proactive approach is necessary for better cost effectiveness, quality and safety. This will involve improvements and modifications at the different life cycle phases; of these, the most essential are the design phase and operation and maintenance phase. A well-designed maintenance philosophy would improve the railway properties and geometry to better handle harsh winter conditions; condition monitoring should also be applied. In addition, it is essential to improve maintenance conditioning in terms of equipment, procedures, logistics, personnel skills and competence for a winter climate (Linné et al. 2012).

Looking at two railway lines, the study finds differences in the number of the railway company's work orders as a function of season and geographical location. It draws the following conclusions:

- Winter problems for line 21 in 2006-07, 2009-10 and 2010-11 can be seen in the historical work order data (Fig. 4). Winter problems in 2009-10 and 2010-11 can also be seen for line 4 but are not as pronounced. Winter problems cannot be found on either line in 2001-02.
- Seasonal differences in the number of work orders (Fig. 4-8) prove to be significant (Tables I and II), answering research question 1.
- The seasonal effect is significantly more pronounced on line 21 than line 4 (Fig. 9 and Table 3), answering research question 2.
- On average, the number of work orders on switches and crossings is 2-3 times greater in winter than in summer for lines 21 and 4 (Fig. 6).
- Modelling the number of work orders as a function of temperature, at system level, proves difficult (Fig. 11, 12 and 16).
- Variations in the number of work orders from one year to another are high, making predictions difficult (Fig. 4, 10 and 14).
- Disregarding snow and ice related work orders, the difference in the number of work orders is about 60% between summer and winter (Fig. 13); it is about 100% when snow and ice problems are taken into account (Fig. 5).
- Studying switches and crossings and disregarding snow and ice related work orders, the difference between summer and winter in the number of work orders is less than 50% (Fig. 15), and 100-200% when snow and ice problems are taken into account (Fig. 6).

Modelling the number of work orders as a function of the temperature at the system level has proven to be difficult. Future study at the component level should therefore be considered.

ACKNOWLEDGEMENTS

The authors would like to thank Dr. Ulla Juntti at Luleå University of Technology/Performance in Cold for comments and input. The authors would also like to thank Luleå Railway Research Center (JVTC), Trafikverket (Swedish Transport Administration), SMHI (Swedish Meteorological and Hydrological Institute) and European project Bothnian Green Logistic Corridor (BGLC) for their support, for making data available and for funding.

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