UNIVERSITY OF SOUTHERN QUEENSLAND

Faculty of Health, Engineering and Sciences

BRIDGE LOAD ASSESSMENT

USING

MACHINE LEARNING

AND

WEIGH-IN-MOTION DATA

A dissertation submitted by

Mike Keenan

in fulfilment of the requirements of

ENG4111/2 Research Project

towards the degree of

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Abstract

Pattern recognition using machine learning algorithms is a mature discipline, but it is still in the research phase in the civil engineering field (Farrar & Worden, 2012). Adding to this body of research contributes to the improvement of our asset management decision-making.

KiwiRail (The New Zealand railway network manager) has an existing process of evaluating axle overloads captured by weigh-in-motion sites that could benefit from further research. This project aims to evaluate how a machine learning model may help.

Overloading is very relevant internationally and has been nominated as one of the top five historical causes of bridge collapse (Zhang et al, 2022). Weigh-in-motion systems capture axle weights and axle spacings but further analysis, such imparted bending moment on any given span length, is a post-processing function. In cases when immediate actions are required following an axle overload then an immediate structural analysis considering also the adjacent axles would be of benefit.

A machine learning model was developed in MATLAB by a process of supervised learning via a simple analytical model constructed in Excel. With enough training data the intent was to obtain an accurate machine learning model such that it could assess a given set of axle loads and spacings and determine if a bending moment limit had been breached or not. A common 6m span length was chosen as the focus area and variables for model input were carefully considered.

As a project outcome a highly accurate machine learning model was established once the training data volume got to approximately 5,000 sets. To get to this stage many variations of training inputs were used and volume of training data was incrementally increased to monitor the effect on accuracy.

A potential future development of this work is to expand the focus area to other span lengths to observe accuracy when more axles are incorporated into the variable set. The analytical model developed for this project was limited to the 6m span length and the required assumptions made it up to 3% non-conservative in outputs. An improved analytical training model is required before the focus area can be expanded.

In conclusion, although moving load analysis lends itself to traditional formula and analytical processing applications this study has shown that a machine learning model may potentially become a viable alternative.

Keywords: *Weigh-in-Motion, Rail Bridge, Machine Learning*

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Limitations of Use

Certificate of Dissertation

I certify that the ideas, designs and experimental work, results, analyses, and conclusions set out in this dissertation are entirely my own effort, except where otherwise indicated and acknowledged.

I further clarify that the work is original and has not been previously submitted for assessment in any other course or institution, except where specifically stated.

Mike Keenan [redacted]

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1 Introduction

Modern societies have enjoyed the benefits that civil structures, such as dams, bridges and power stations, have given us. As these systems move towards the end of their original design lives, economical solutions are required to meet new demands and to manage risk. Structural health monitoring (SHM) is a growing field to cater to this need, and at the heart of this field is data. The use of computers to process this data in beneficial ways is increasing all the time and machine learning is at the leading edge of this.

Pattern recognition using machine learning algorithms is a mature discipline, but it is still in the research phase in the civil engineering field (Farrar & Worden, 2012). Adding to this body of research contributes to continuous improvement of our asset management decision making.

KiwiRail (The New Zealand railway network manager) has an existing process of evaluating axle overloads captured by weigh-in-motion systems that could benefit from further research. This project aims to evaluate how a machine learning model may help.

1.1 Background

There are approximately 1,500 rail bridges in the New Zealand rail network with an average age approaching 80 years. Asset condition and capacity has been managed to meet the operating load service requirements as they increase over time. Having awareness and understanding of bridge capacity is important on one hand, just as having knowledge of loading is important on the other. Weigh-in-motion sites are installed throughout New Zealand as a mitigation tool for managing the risk of overloaded wagons. While overloads are undesirable they can happen and processes are in place to respond to such occurrences.

In the existing overload response process there is a time lag between when a moving force (axle load) is recorded and when this load can be structurally evaluated. If this axle load is above a certain threshold, then conservative protocol is immediately adopted which can have significant commercial implications for the business. Often by the time structural evaluation occurs the train controller may have had to make several operational decisions, such as:

- stopping the train from continuing
- assessing the train driver’s hours and arranging replacement staff
- contacting customers and rearranging freight movements

- arranging the structure inspectors to undertake inspections (for safety reasons these only occur during daylight, so the line is at least closed until then).

The commercial implications of such an event would be in the tens of thousands of dollars plus the reputational damage in the eyes of the customer.

More immediate analysis of loads could potentially reduce conservatism and therefore reduce the need for temporary line closures.

Load evaluation of moving forces over bridge structures has a historical bias towards analytical methods because established stress evaluation formulae can be combined with given variables to produce accurate results. Machine learning as a method of load evaluation has therefore not been required, but that is not to say that it cannot be an effective alternative.

1.2 Project aim and objectives

This project aims to establish if algorithms based on a machine learning model can be an effective alternative to an analytical model for evaluating axle loads over bridge structures and for providing real-time advice following an axle overload, i.e., ***'ok to proceed'*** or ***'not ok to proceed'***.

The objectives of this project are to:

- develop an analytical training model for axle load assessment, and
- train a machine learning model for axle load assessment.

1.3 Research significance

The expected benefits of this research include, but are not limited to:

- an advancement in the body of research regarding application of machine learning in the civil engineering field, and
- a reduction in railway line closure following individual train axle overload.

An advantage of rail loading, as opposed to road, is that the exact location of the loads on the structure are known. They are confined to the line of the tracks and the defined axle separation of the train vehicles. Patterns in allowable loading considering variables of both axle loading and axle spacing may be established. This could be of benefit because certain wagons (i.e. those with larger spaces between axles) may be evaluated as ‘ok to proceed’ even if they are loaded higher than more squat wagons. This could enable wagons that are capable of higher axle loads to realise their capacity potential and therefore make more revenue.

Further to this point, James (2003) proposes a concept where customers prepared to weigh their loads can be allowed a higher axle load. This could be differentiated dependent upon the wagon type used.

1.4 Dissertation structure

This dissertation is divided into seven chapters. Each chapter details a key process undertaken to achieve the specified project aims. The structure of this dissertation is briefly explained below:

Chapter 1: Introduction

Chapter 1 introduces the subject matter of this dissertation and provides a brief background regarding the project context within the New Zealand railway environment. This is followed by highlighting the significance of this research and outlines this project’s aims and objectives.

Chapter 2: Literature Review

Chapter 2 reviews the history of rail bridging in New Zealand and the tools and processes in place for managing loading. Current and historical analytic techniques and machine learning application is also reviewed to assess and determine applicable strategies for resolving this project’s aims and objectives.

Chapter 3: Methodology

Chapter 3 details the methodology in which this project will be delivered. It also describes the definition of a focus area and process by which to meet the project objectives.

Chapter 4: Analytical model development

Chapter 4 describes how the analytical model was developed and provides the results of this process. The analytical model is the key tool for providing training data for the subsequent machine learning model.

Chapter 5: Machine learning model development

Chapter 5 describes how the supervised machine learning model was developed and the results and iterations.

Chapter 6: Discussion

Chapter 6 examines the results in more detail. Limitations of the study are discussed along with details as to how this project advances the field of industry.

Chapter 7: Conclusion

Chapter 7 concludes the achievements of the research with respect to satisfying the project aims and objectives. The capacity for future works is also discussed with recommendations.

2 Review of literature

This section will review literature in the following areas:

- weigh-in-motion context
- analytical moving load models
- machine learning models.

2.1 Weigh-in-motion context

This section contains further review of the background to better convey the context of the study, from the rail bridge history through to the overload axle response process.

2.1.1 Rail bridge construction history

There are approximately 1,500 rail bridges in New Zealand with a total bridge length of more than 60 km and an average bridge age approaching 80 years. The construction date profile is shown in Figure 1.

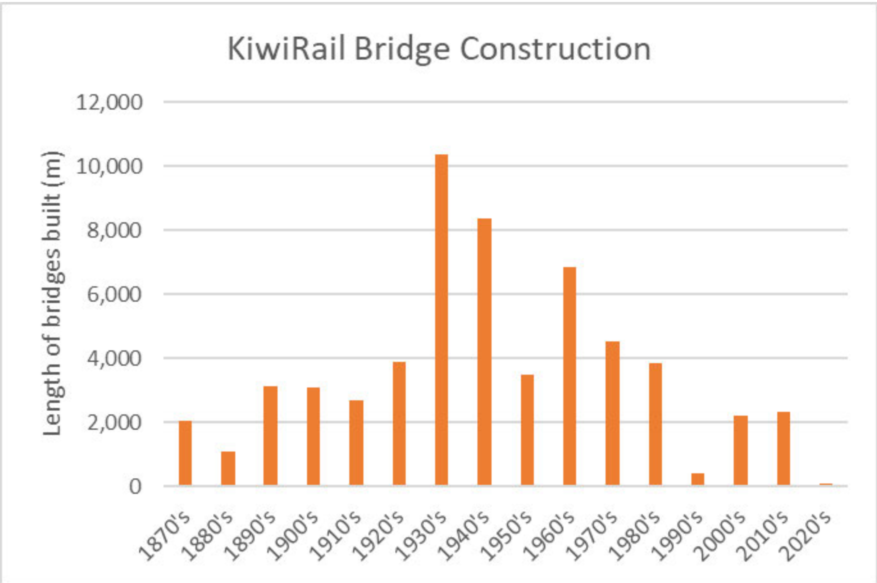

Figure 1: Bridge length, per year constructed

2.1.2 Rail bridge rating

The design standards and construction material have been variable over time and at the same time the operational demand for the network has increased. At each step change along the way the bridging capacity has been subject to assessment of its fitness for purpose. Currently KiwiRail bridges are strength rated using a concept called Maximum Rating, as prescribed in AREMA code. This has been the codified process since 1994 and it essentially translates to a utilisation of 0.8 of the material yield strength.

KiwiRail adopts the Maximum Rating concept for their load assessment of structures based on two main reasons:

- KiwiRail has a rigorous inspection regime, and
- the load cycles are not significant and fatigue evaluation of structures on the line have been undertaken to identify the risk structures.

2.1.3 Overloads and low-strength bridges

The other significant aspect to note, aside from fatigue implications, is that of strength. When the allowable stress is relatively high then occasional overloads can be more problematic. Increasing instances of timber pier cap failures occurred around the late 1990s and early 2000s.

2.1.4 Capital investment

The Crown took ownership back of the network in the early 2000s and consequently investment in the aging infrastructure proceeded. In fact, all the bridge length observed in Figure 1 constructed after the year 2000 related directly to the replacement of bridges with life-expired timber piers. This amounted to more than 4,000 m of bridge replacement containing approximately 800 timber piers. There remains twice this number of timber piers still on the active network. As part of the network upgrade the timber caps and spans were given a more in-depth strength assessment and assigned a capacity rating. A better understanding of the loads was also sought and that is where the weigh-in-motion sites came in.

2.1.5 Weigh-in-motion sites

A mitigation tool that was put in place, and one most relevant to this research project, was the installation of weigh-in-motion sites for the management of overloads.

Figure 2: Rolleston coupled weigh-in-motion site

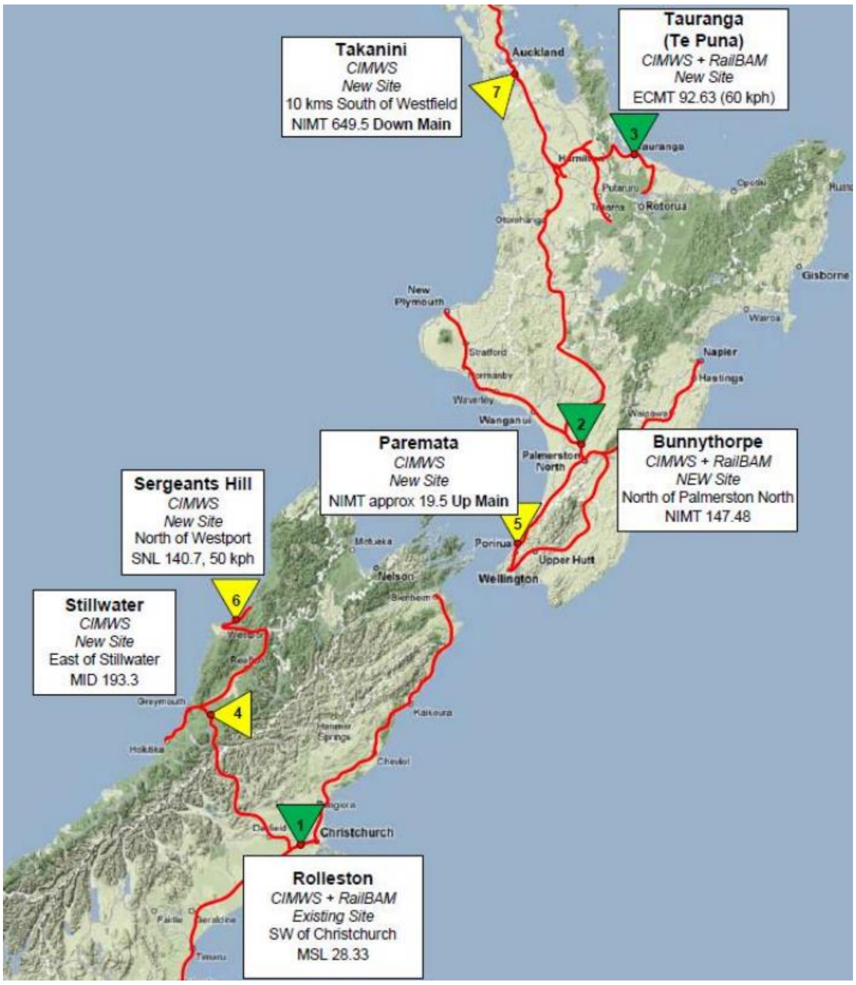

Figure 3: Coupled weigh-in-motion sites nationwide

This system records every axle load and the spacing between them. A trigger action response plan has been codified whereby specific actions are taken based on varying degrees of axle overloads. The response sometimes involves the closure of a line while offending wagons are removed and bridges are inspected, based on a pre-populated, conservative listing.

2.1.6 Evaluation of overload

The process following a wagon overload is shown in Figure 4.

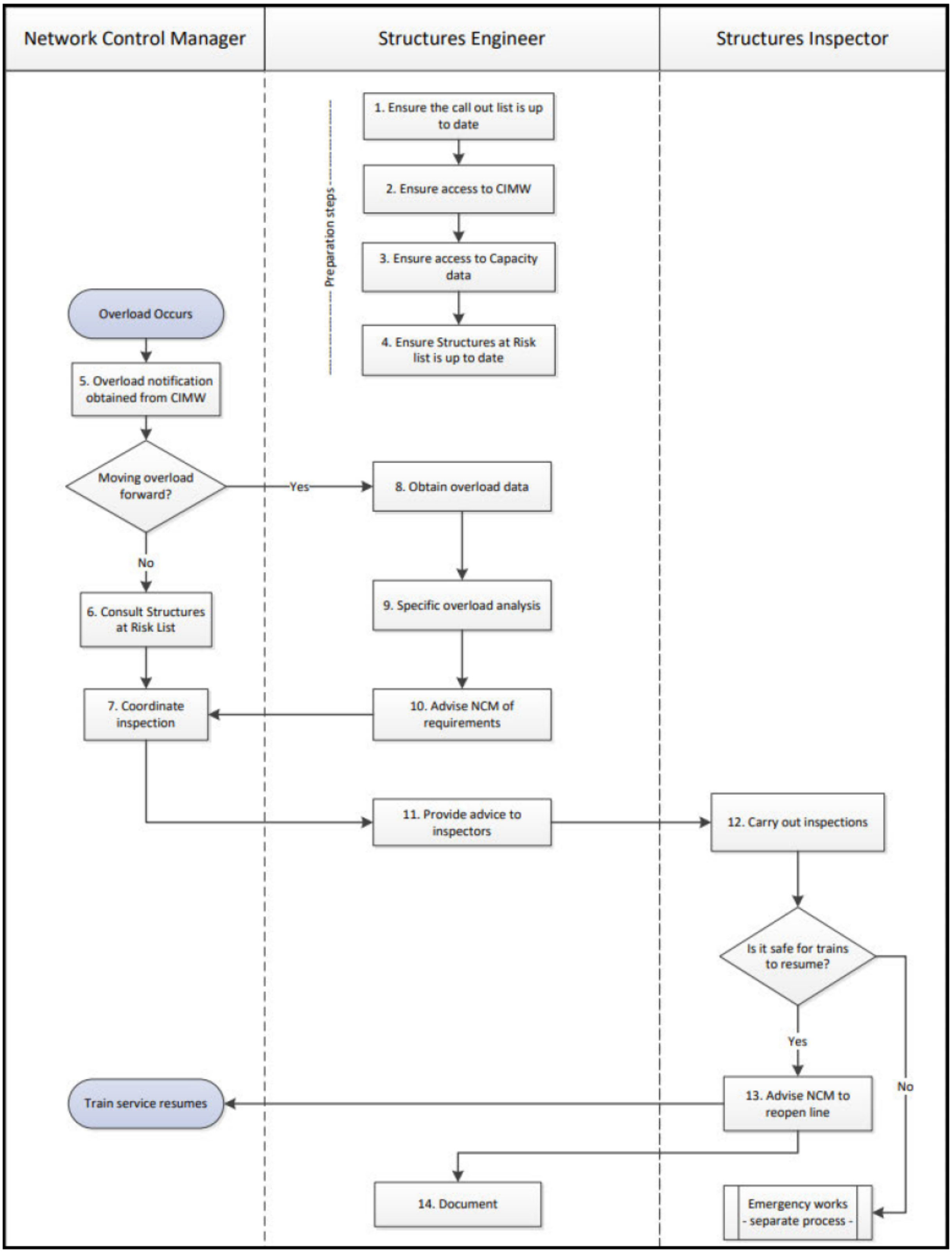

Figure 4: Structural evaluation of overload process

The railway line is closed for 12 to 24 hours while this process occurs. At the same time as the engineer is analysing the overload data the train controller is arranging for the removal of the overloaded wagon and inspection of the line based on a conservative pre-populated ‘Structures at risk’ list.

There are occasions when the structural analysis shows that the overload was not any more of a demand on the bridges than the ordinary passing of a locomotive. By this stage often decisions have been made, and there is still a perception that an axle overload is a structure overload.

Given the historical context and relatively low factor of safety on KiwiRail bridges the need for monitoring of overloads is justified. However, basing all trigger response actions on axle loads alone sometimes results in closing the railway line and incurring costs unnecessarily.

2.1.7 Overloading abroad

The accelerated damage on infrastructure from overloaded axles is not unique to New Zealand, or indeed the railway system. Weigh-in-motion data was used in a study that examined vehicle overloading in Pakistan (Raheel et al, 2018). Overloads are a well-studied and known cause of premature failure of pavements. Rather than a response process involving any immediate network closure and inspection, the study recommendations point towards design. The study concluded that axle configuration and axle load are the most important variables and therefore truck designs with the most sympathetic configurations were recommended along with increasing pavement thickness.

Overloading is very relevant internationally and has been nominated as one of the top five historical causes of bridge collapse (Zhang et al, 2022; Figure 5), particularly as bridges age.

Figure 5: Bridge failures due to overload (Zhang et al, 2022)

2.2 Analytical moving load models

There are several analytical methods used to convert axle loads and spacings into a range of span bending moments and shear forces.

The techniques outlined in a structural requirements document (Young, 2011) prescribed the following typical methods:

- principle of superposition
- method of sections
- method of functions.

This last method is currently used by KiwiRail for the purpose of evaluating given train configurations and the granting of running rights. It is discussed in the next section.

2.2.1 Method of functions application

In 2011, an application called Cognos was developed by Cortell Consultants for KiwiRail to undertake moving load analysis on any given equipment configuration, including specified overloaded wagon configurations. Information found online (element61, 2021) describes IBM Cognos TM1 as an On-Line Analytical Processing software tool with a multidimensional analysis application known as the OLAP cube (Figure 6).

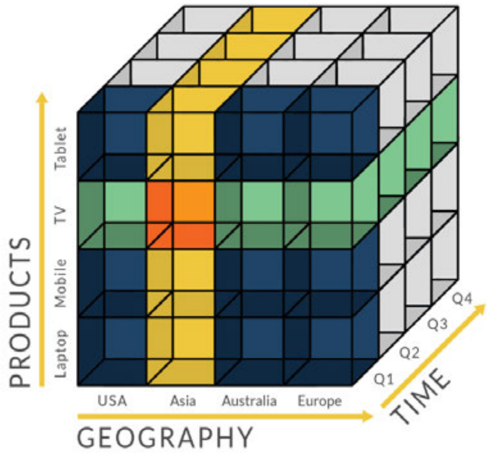

Figure 6: Illustration of an OLAP cube (Chin, 2020)

This is the tool that has been available for the last 10 years to the structural engineer for undertaking step 9 in the process shown in Figure 4. It requires an engineer, available around the clock, to manually type axle loads and spacings into rows on a single input screen with a limit of six axle load inputs (Figure 7).

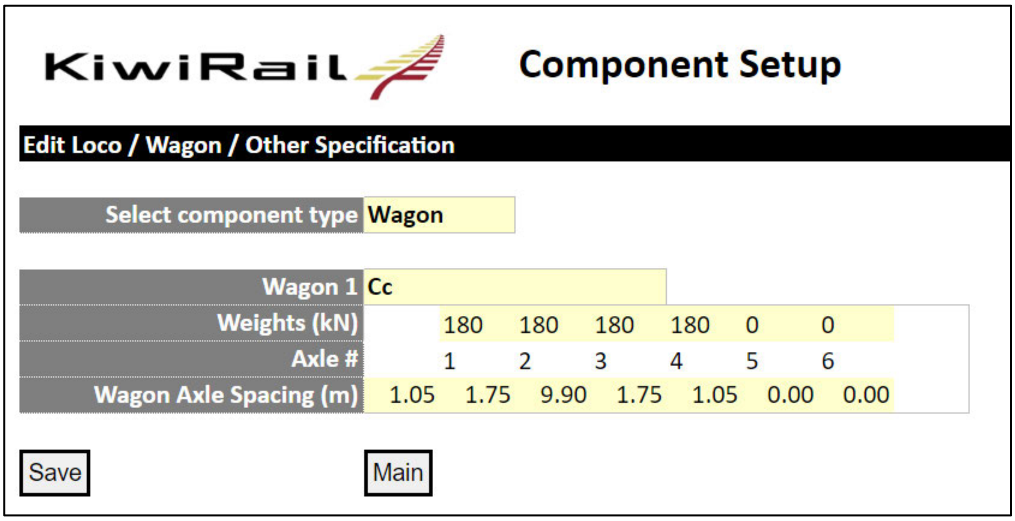

Figure 7: Component input screen for KiwiRail Cognos tool

It is therefore not practical to use for developing a large volume of results as is best for supervised learning. Going back to the vendor to redevelop the application is an option; however, the online analytical processing (OLAP) cube, such as that utilised in the Cognos application, has been moved away from (Chin, 2020). The main reasons given for this is that memory is cheap and computing power is readily available. Fifteen years ago, a moving force simulation could involve up to three weeks of continuous simulation per span (James, 2003). Modern computing power makes this now less of an issue.

Columnar databases can perform similar workloads to OLAP cubes at equally good performance (Chin, 2020). It is also concluded that most columnar databases have settled on SQL as the query standard.

Aside from Cognos, there are many moving load analysis software packages available, such as STAAD Pro, SAP and LUSAS. While implementing an improved analytical model for overload response is an avenue to explore, the purpose of this research is to establish the effectiveness of a machine learning model in this environment. Therefore, an analytical model that is simple to apply to thousands of rows of axle load data for the purpose of creating a supervised machine learning environment that can automate the analysis is the basic requirement for this project.

2.3 Machine learning models

2.3.1 Machine learning in general

Machine learning as a field started to flourish in the 1990s and has been on the rise ever since. The songs that music applications suggest to users is based on machine learning that recognises patterns of listening behaviour. The social media business model is built on machine learning. To quote Edward Tufte from the documentary *Social Dilemma*: "There are only two industries that call their customers 'users': illegal drugs and software", meaning our profile and behaviours are being used to train machine learning models and algorithms to keep us, the customer, engaged. It is all about pattern recognition and prediction.

In the field of civil engineering and science there are examples of machine learning in various stages of research and implementation. Hydrologists are researching using deep learning by way of video analysis and a rising bubble method to establish an automated calculation of river discharge rate (Bulleid and Wilding, 2019). In another example, video analysis and machine learning is being implemented for the purpose of identifying target weeds for eradication from waterways (Bulleid and Clements, 2021).

Another innovative product that has progressed past research into a commercial venture is VAPAR. It is an automated condition assessment tool that combines CCTV footage and machine learning to classify defects in pipelines (Palmer-Derrien, 2021). The innovative nature of VAPAR is an auto-coding algorithm that can quickly take large volumes of imagery and assign defect categories to it automatically. In this way it can provide more consistent and comprehensive information from which better investment decisions can be made.

VAPAR now processes over 200 km of wastewater pipes for dozens of clients. Considering that the total global length of wastewater infrastructure is massive, this represents a very insignificant market share presently. For example, the United Kingdom-based company United Utilities manages a network of approximately 80,000 km (Vapar, 2019). However, as the technology becomes proven more consistently and widely, the potential for exponential growth exists. The market approach is key to capturing that untapped market.

What is given in this section is a small sample of machine learning examples to illustrate that machine learning is here and the use of it will only increase with time. The next section describes examples relevant to this specific research topic.

2.3.2 Machine learning for moving force models

Little research has been found regarding machine learning and moving load analysis. Supervised machine learning "can be much more readily accomplished for rotating machinery" (Farrar & Worden, 2012).

Perhaps the lack of research can be explained by the fact that there hasn't been a need. Where input variables are given and standard formulation is available, then alternatives to an exacting analytical model can be rationalised away as surplus to requirements.

Separate to analysing records of loads from weigh-in-motion systems, attempts to instrument structural elements themselves have come up against difficulties not encountered in the likes of a controlled machine room: the impracticalities of access and safety, to name but two. The vastness of a structure is another consideration. Installing permanent systems for acquiring data from a bridge can come at a significant cost.

Analysing loading data presents a cheap alternative to instrumenting the structure itself, and while it cannot convey the response of the structure, the imparted loading effect is just as important to understand. And the loading data is readily available in vast quantities as a simple set of forces and distances between them.

Ways in which to develop a machine learning model for this application have been researched and introducing flaws into a computer simulation has been one such idea (Farrar & Worden, 2012). Potentially something along these lines could be adopted in this research in a 'ok to proceed / not ok to proceed' manner rather than flawed/non-flawed. The classification learning application is likely a good method to proceed with in this case.

Examining the available data and critically assessing how best to utilise the variables to create an accurate machine learning model is the challenge. Adjusting the manner in which the data are viewed is something James (2003) illustrated with the concept of converting data from distances and forces into turning points. Critically assessing along the way what are the key variables and how to present them is a key consideration for this project.

3 Methodology

The project objectives will be delivered by the following steps, which are elaborated upon in subsequent sections:

- Define the focus area – narrow down parameters to establish a focus area for the research project.
- Develop an analytical load evaluation model – to enable pre-processing of weigh-in-motion data such that it can be used for supervised machine learning.
- Develop a machine learning model – process the data, test, adjust, repeat.

3.1 Define the focus area

If it is assumed that an arbitrary train length is 100 m and the idea that this is evaluated for any given span as it moves across at 0.1 m intervals, then there are 1,000 calculations to perform for this train. To evaluate for a range of spans at 0.5 m increments from 2 m to 80 m span length then to assess any given train over all possible span length options is in excess of 150,000 calculations for one train record. And weigh-in-motion data is available for many thousands of trains. It clearly requires a targeted set of parameters to be defined to allow an entry point into this research.

3.1.1 Select a span length

A common span length that has been installed on the New Zealand rail network is the 20' (6 m) long steel plate girder (SPG) span. Using this as the default span length will assist in simplifying the study.

3.1.2 Select a load configuration

Over the course of time a large variation in the axle spacings between the various locomotives and wagons has developed. Ignoring the locomotive and using a common wagon configuration for which there is plenty of data available to work will best suit the study. With these focus areas defined, the points of interest become those as shown in the box in Figure 8.

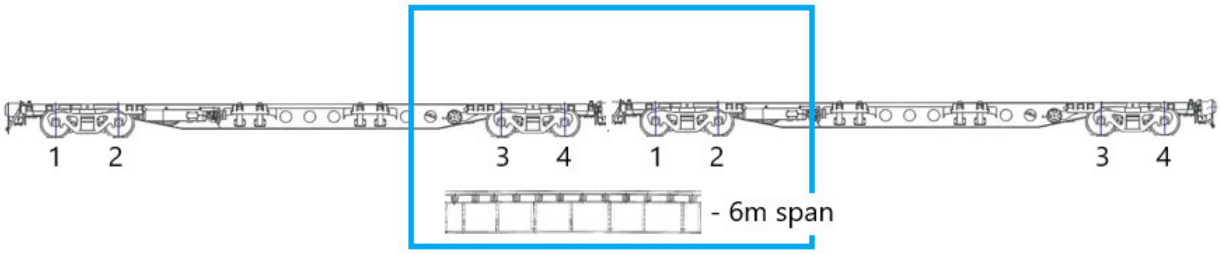

Figure 8: Study focus area

3.1.3 Stress of choice

A further definition to focus the study is to select the type of stress to consider from the given loads. Typically, spans are rated for both shear force and bending moment capacity and these are compared with the shear force and bending moment from the applied load. For the purpose of simplification, this study will focus on bending moment stresses only as the bending is the governing stress in these typical girders.

3.2 Plan for an analytical model

For the purpose of this project an analytical model is required to be developed that can pre-process data to allow supervised machine learning and testing to occur.

3.2.1 Available data

Permission to use real data has been granted and a large volume of historical data are available in Excel form, as shown in the example in Figure 9.

Train Time	Site	Train Axle	Vehicle Axle	Axle Pitch (mm)	Axle Speed	Axle Weight (t)
2022-01-21 15:27:29	Stillwater	34	3	1770	40.68	16.13
2022-01-21 15:27:29	Stillwater	35	2	8600	40.32	17.02
2022-01-21 15:27:29	Stillwater	36	1	1750	40.68	17.29
2022-01-21 15:27:29	Stillwater	37	4	2080	40.68	16.21
2022-01-21 15:27:29	Stillwater	38	3	1770	40.68	15.55
2022-01-21 15:27:29	Stillwater	39	2	8630	40.32	16.91
2022-01-21 15:27:29	Stillwater	40	1	1750	40.32	17.19

Figure 9: Sample of data exported from weigh-in-motion site

3.2.2 Model selection and plan

With a large volume of Excel data available, with axle pitch and axle weight arranged in columnar form, a pragmatic method to develop the analytical results required would be an Excel model integrated into the axle load data, row by row. The following steps are planned to be implemented into the Excel model:

- Establish, by means of a series of 'if 'statement columns, the rows that have axle groups in the defined study focus area from Figure 8
- Use the principle of super position method to establish the maximum bending moment as the axle on the row of interest is upon the span.
- Establish a result of *'ok'* or *'not ok'* column for the axle when it is considered as a group, rather than an individual axle.

3.3 Plan for a machine learning model

With a set of data ready for import the development of a supervised machine learning model can begin. The method used to undertake this development is shown in Figure 10.

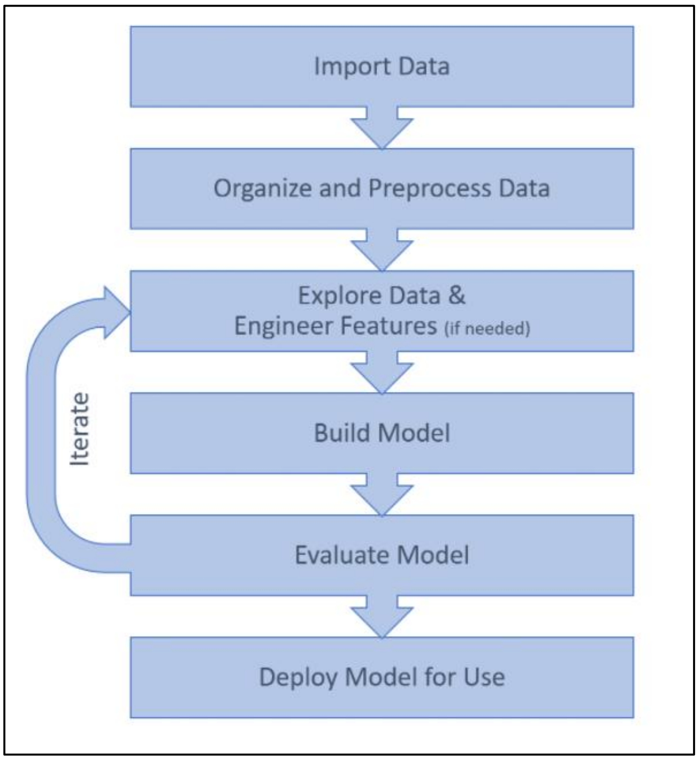

Figure 10: Overview of the classification workflow (Matlabacademy, 2021)

3.4 Risk assessment

A preliminary risk assessment has been completed as is available in Appendix B.

3.5 Project resources

Resources required to complete this project are:

- Weigh-in-motion datasets obtained from KiwiRail weigh-in-motion supplier, Track IQ
- Permission to use weigh-in-motion data for this research project
- MATLAB R2021a programming software including the machine learning module
- Microsoft Excel.

4 Analytical model development

A sophisticated analytical moving load programme is surplus to requirements for this project and a simplified Excel model applied directly to the weigh-in-motion data export has been developed. This model will rely on some assumptions, for the purpose of simplification, but will result in a large dataset with results of ‘ok’ and ‘not ok’ axles identified to an acceptable level of accuracy for the purpose of the project.

4.1 Principle of superposition

A model was developed in Excel whereby the principle of superposition was utilised directly on the weigh-in-motion data file. A series of ‘if’ statements was used to target the axles shown in Figure 8. At this stage in development a simplification was required which meant taking forward this assumption:

- The maximum bending moment will occur at mid-span.

This assumption will require testing, but it allowed the developed formula to be transposed to every recorded axle load, row by row. The formula first identified if the row axle was from the focus area. If it was, it was assessed as being located at mid-span with contributions from rows above and below contributing to the mid-span moment in the same manner as P1 and P3 in the concept shown in Figure 11.

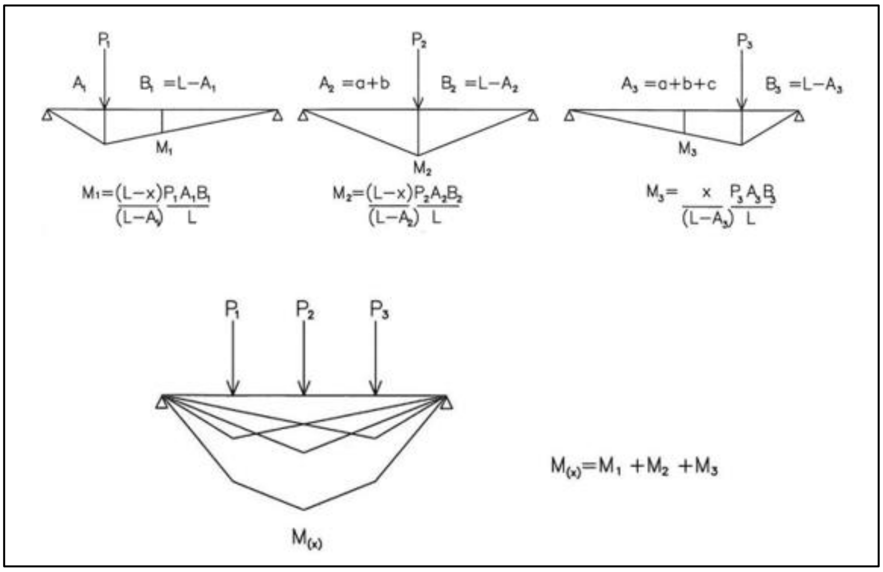

Figure 11: Principle of superposition

When the formula cells were added to the Excel load file it now returned total bending moment stress as each axle landed on the middle of the 6 m span. The largest bending moment is when either of the center two axles are at mid-span, as at this point there were three axles contributing. This can be seen in Figure 12, with the colour scheme showing the contribution of adjacent rows to the row that is being summed.

axle no.	weight (KN)	BM contribution at Midspan (KN.m)	Combined BM at Midspan (KN.m)	axle BM at Midspan (KN.m)	Combined BM at Midspan (KN.m)	axle BM at Midspan (KN.m)	Combined BM at Midspan (KN.m)	axle BM at Midspan (KN.m)	Combined BM at Midspan (KN.m)	Mid span BM when axle at midspan (KN.m)	% of load allowance
3	177	265.5	(=) 377.9	112.4	0.0	0.0	0.0	0.0	0.0	**377.9**	81%
4	177	(+) 112.4	0.0	(+) 265.5	(=) 466.4	88.5	0.0	0.0	0.0	**466.4**	100%
1	177	0.0	0.0	(+) 88.5	0.0	(+) 265.5	(=) 466.4	112.4	0.0	**466.4**	100%
2	177	0.0	0.0	0.0	0.0	(+) 112.4	0.0	(+) 265.5	(=) 377.9	**377.9**	81%

Figure 12: Analytical model using principle of superposition

If it is taken that the line axle load allowance is 177 kN (18t) then the resulting bending moment can now be set as 100% load allowance. This bending stress can be set as the control stress to which all other load configurations are compared. Note that when the first and last axle are at mid-span then only 81% of this load allowance is utilised.

An online bending moment tool was used as a calculation check and this confirmed the model accuracy with the given assumptions and input parameters resulting in the same maximum bending moment stress of 466.4 kN.m (Figure 13).

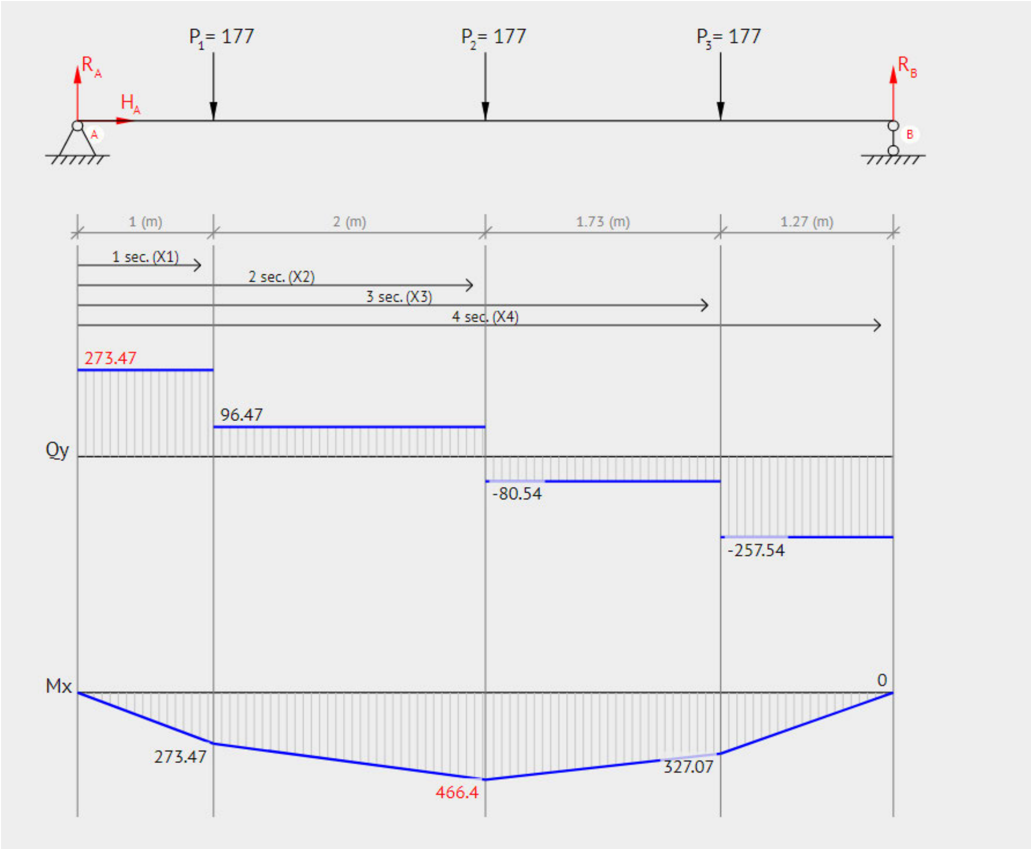

Figure 13: Control model calculation check (beamguru.com/online/beam-calculator/)

An initial check of the assumption about the maximum bending moment occurring at mid-span was made by running the loads through the Cognos tool. This tool incrementally evaluates the specific load over the length and returns the maximum bending moment irrespective of where it occurs on the span. The maximum bending moment is found to be 466.57 kN, as shown in Figure 14.

Wagons						
Weight (kN)		177	177	177	177	
Axle #		1	2	3	4	
Spacing (m)	1.00	1.73	6.85	1.73	1.00	
Span Length	E40 Moment (kNm)	Vehicle Moment (kNM)	E. Vehicle Moment	E40 Shear (kN)	Vehicle Shear (kN)	E. Vehicle Shear
3.5	196.57	175.56	35.7	302.09	266.51	35.3
4.0	263.40	217.45	33.0	331.08	289.40	35.0
4.5	330.14	267.51	32.4	353.63	316.24	35.8
5.0	396.84	333.86	33.7	387.33	337.72	34.9
5.5	463.62	400.22	34.5	416.84	356.57	34.2
6.0	544.01	$\boxed{466.57}$	34.3	441.44	385.86	35.0
6.5	631.60	532.94	33.8	462.25	410.64	35.5
7.0	719.56	604.08	33.6	480.09	431.88	36.0

Figure 14: Cognos moving load model application

The non-symmetry of loads in the study focus area accounts for the small difference (466.4 kN.m vs 466.57 kN.m), with this maximum moment likely to occur just to the side of mid-span. It can be concluded, however, that the error introduced by this assumption is negligible. This assumption should be revised again later when loads and spacings vary more.

4.2 Variable assignment for classification

An important step in pre-processing is the delineation of axles in the focus area to a status of either *'ok'* or *'not ok'*. As the instances of actionable overloads (those more than 15% over the assigned axle load limit) are few, the load limit of 18 t itself will be used for no reason other than it will provide a larger *'not ok'* status dataset to use for supervised machine learning.

The hypothesis is:

- The percentage overload of an axle does not correlate to the same percentage overload of a structure.

This is best illustrated by using an example from the model. Figure 15 shows an example of an axle that is greater than 18 t and therefore appears to be an overload, yet when it is evaluated as a group the bending moment it induces on the structure is less than the control group given in Figure 13.

Axle Weight (t)	Mid Span BM	% of load allowance
17.58	366.8	79%
17.78	454.7	98%
18.60	458.5	99%
17.24	371.8	80%

Figure 15: Overloaded axle that does not correlate to overloaded structure

Therefore, the group of four axles in Figure 15 would constitute an example set of variables that can be taken forward to the supervised machine learning model as *'ok'*.

4.3 Axle load distribution over bogie

Upon development of model it became a curiosity as to why each axle on a bogie returned a similar but slightly different axle load. Examining a total of 3,600 axles gave an interquartile range within +/- 4%

Upon speaking to KiwiRail wagon designers it was confirmed that the design is based on spreading the load evenly across the two axles. Discrepancies can occur when brakes are activated but otherwise the two loads should be considered equal.

The application of the loads was thus reduced from four variables to two as per the following figure:

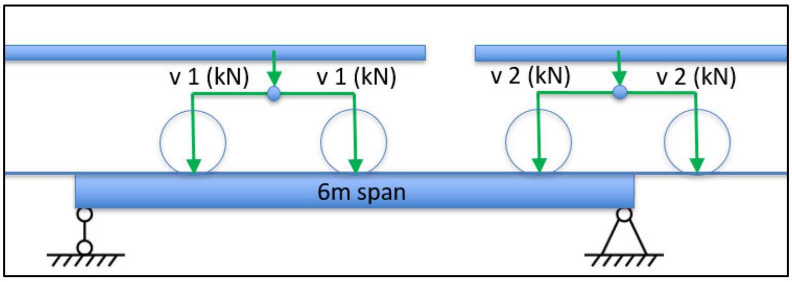

Figure 16: Variable assignment for loads

This is an example of critically assessing the variables in an attempt to reduce them and keep only key variables. The weigh-in-motion axle load data could now be applied to the model. The distance between the loads was considered next.

4.4 Axle spacing distribution

A sample of 3000 wagons of all types was taken from the weigh-in-motion data to establish a set of variables for the axle spacings. The bogie axle spacing, shown as v 3 in Figure 17, had small variation compared with the wagon axle spacing, shown as v 4. The variability in the sample can be seen in Figure 18.

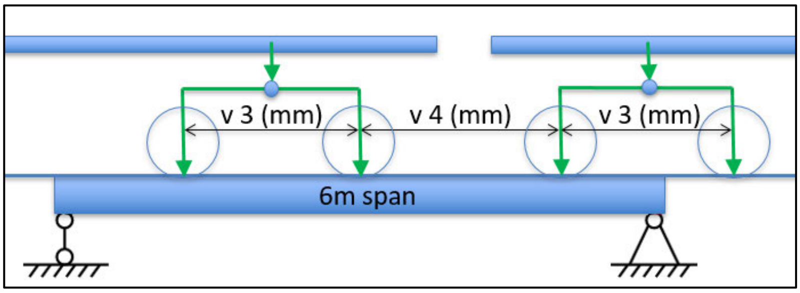

Figure 17: Variable assignment for spacings

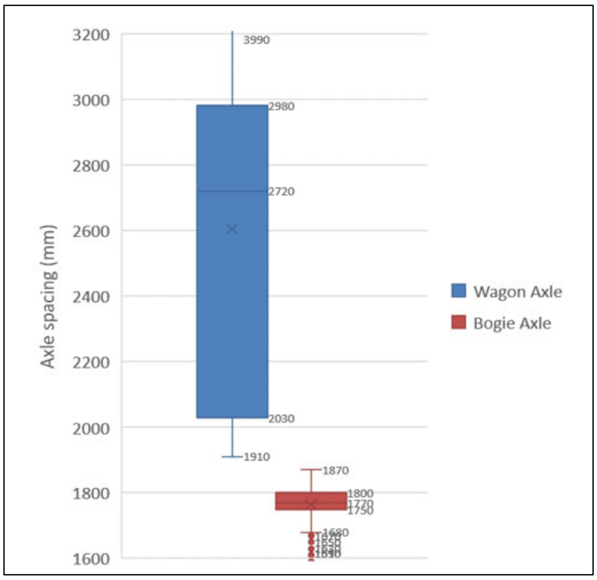

Figure 18: Range of spacings for wagon and bogie axles

To enable development of a training data set that covered an appropriate range of axle spacings a methodic process was followed. The variations in wagon and axle spacing were broken into the following inputs:

- variable 3 Bogie axle – 1650, 1700, 1750, 1770, 1800, 1850
- variable 4 Wagon Axle - 1900, 1950, 2000, 2010, 2050, 2100, 2200, 2500, 2800

The analytical training model could now be developed.

4.5 Analytical model output

The analytical model was applied to the data set containing a wide range of loads, both under and over the 18t set limit. The spacing variables were set to a specific combination and the results exported. The spacing variables were then adjusted multiple times until model outputs for every combination as per the following table was established:

v 3 – axle spacing (mm)	1850	✔	✔	✔	✔	✔	✔	✔	✔	✔
	1800	✔	✔	✔	✔	✔	✔	✔	✔	✔
	1770	✔	✔	✔	✔	✔	✔	✔	✔	✔
	1750	✔	✔	✔	✔	✔	✔	✔	✔	✔
	1700	✔	✔	✔	✔	✔	✔	✔	✔	✔
	1650	✔	✔	✔	✔	✔	✔	✔	✔	✔
		1900	1950	2000	2010	2050	2100	2200	2500	2800
		v 4 - wagon spacing (mm)								

Figure 19: Matrix of spacing combinations for model development.

The final analytical model file consisted of approximately 200,000 axle rows evaluated as 'ok' or 'not ok', each based on the loads and spacings between them.

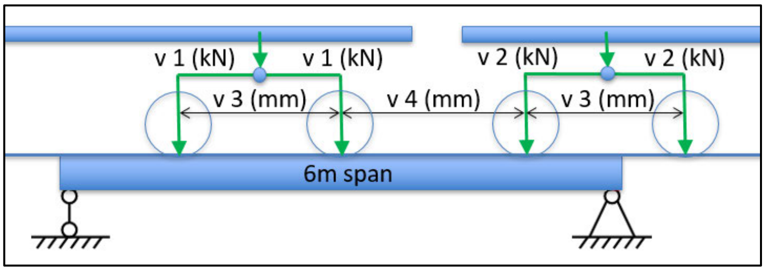

Figure 20: variables assigned

Using the method of superposition each row was evaluated with given variables and the percentage of resulting bending moment compared to the control established. If any axles across the group exceeded 100% then the four variables used as part of that group were displayed in column assigned as 'not ok' (Figure 21).

wagon no.	axle no.	axle (t)	% of control	'ok' column	'not ok' column		variables	'ok' column	'not ok' column
CE 002547	2	18.1	82%	18.1	0		v1 =	18.1	0
CE 002547	1	18.1	99%	18.1	0		v4 =	2100	0
CE 003045	4	17.8	98%	17.8	0		v2 =	17.8	0
CE 003045	3	17.8	80%	17.8	0		v3 =	1750	0
CE 003045	2	18.4	83%	0	18.4		v1 =	0.0	18.4
CE 003045	1	18.4	101%	0	18.4		v4 =	0.0	2100
CE 003736	4	18.3	100%	0	18.3		v2 =	0.0	18.3
CE 003736	3	18.3	83%	0	18.3		v3 =	0.0	1750

Figure 21: developed analytical model with an overload identified

The second group of axles from Figure 21 can be seen again in Figure 22, this time moving into the 'ok' column due to the increase in axle spacing and subsequent reduction in bending moment.

wagon no.	axle no.	axle (t)	% of control	'ok' column	'not ok' column		variables	'ok' column	'not ok' column
CE 003045	2	18.4	82%	18.4	0		v1 =	18.4	0
CE 003045	1	18.4	98%	18.4	0		v4 =	2200	0
CE 003736	4	18.3	97%	18.3	0		v2 =	18.3	0
CE 003736	3	18.3	82%	18.3	0		v3 =	1800	0

Figure 22: changing spacing changes the model outcome

The completed data set to take forward to machine learning training constituted approximately 42,000 sets of variables in the 'ok' column and 6,000 sets of variables in the 'not ok' column.

5 Machine learning model development

The classification learning application within MATLAB software was used. This section presents the process as described in the methodology section and repeated here:

- organise and pre-process data
- build model
- evaluate
- iterate.

5.1 Organise and pre-process data

The Excel file, complete with the analytical results including the ‘ok’ and ‘not ok’ assignment was uploaded to MATLAB. An m file was developed in MATLAB to rearrange the data into rows (Figure 23) such that each row contained a set of variables and a result assignment.

DataGeneration.m

```
%initial data generation code written by Yang Yu 20 Feb 2022
%uses the 2 trailing axles of one wagon and the 2 initial axles of the next

clear;clc;close all
data_okload=xlsread('Data.xlsx',1,'Y2:Y7000');
data_overload=xlsread('Data.xlsx',1,'Z2:Z7000');
updated_data_okload=data_okload(~isnan(data_okload));
updated_data_overload=data_overload(~isnan(data_overload));
new_data_okload=reshape(updated_data_okload,[4,length(updated_data_okload)/4]);
new_data_okload=new_data_okload';
new_data_overload=reshape(updated_data_overload,[4,length(updated_data_overload)/4]);
new_data_overload=new_data_overload';
input_data=[new_data_okload;new_data_overload];
label_okload=ones(size(new_data_okload,1),1);
label_overload=zeros(size(new_data_overload,1),1);
output_data=[label_okload;label_overload];
train_data=[input_data output_data];
save('train_data','train_data')
```

Figure 23: Data generation ‘m’ file

The train data file could now be developed following the running of this code. It was constructed of rows containing the four variables with the focus area along with a fifth classification indicator. The classifier ‘1’ is for load groups that are *‘ok’* and ‘0’ for load groups that are *‘not ok’*. Example rows are shown in Figure 24.

48168×5 double

	1	2	3	4	5
42186	5.3845	2200	5.4725	1750	1
42187	5.3845	2200	5.6155	1750	1
42188	18.4470	2200	18.4030	1750	1
42189	18.3535	2200	18.6670	1750	1
42190	17.8700	1900	17.4200	1650	0
42191	17.6900	1900	16.7350	1650	0
42192	17.2450	1900	17.4550	1650	0
42193	18.1200	1900	17.1850	1650	0

Figure 24: sample of data file organised for model input

With the data now organised for loading into the classification learning application it was exported and a random number assigned to an adjacent column. A random sample of 10,000 rows was removed (approximately 20%) to use as the test set. The rest was taken forward to train the model.

5.2 Build the model

The train data were imported into the classification learner application and the model as shown in Figure 25.

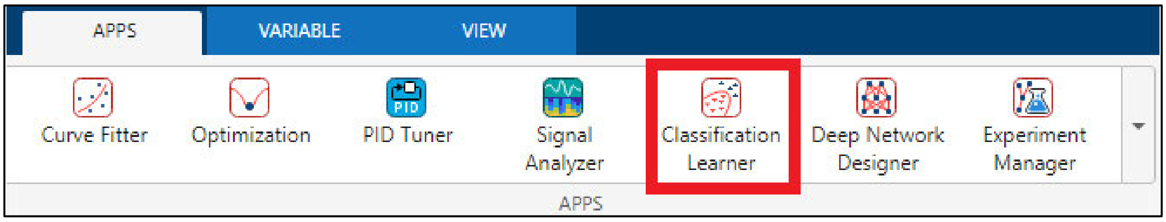

Figure 25: classification learner application

Various classification learner models can be selected to learn the result pattern and after user testing three were selected to evaluate: the decision tree, the k-nearest neighbor and the Neural Network.

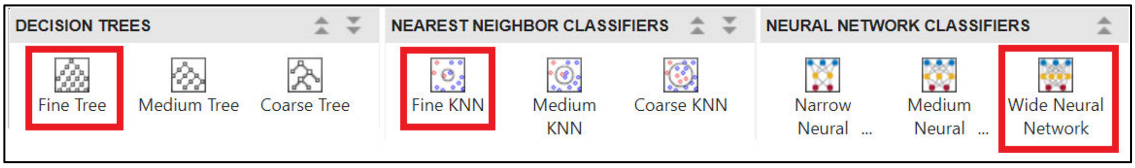

Figure 26: classification models selected for project

An initial training set of just 50 rows, randomly taken from the training data, was used and the three models were trained.

5.3 Evaluate the model

Upon training, the model assigns a validation score to indicate how close the trained model predications are to the 'true' cases, these true cases being the *'ok'* or *'not ok'* assignments given at the analytical model stage. A validation confusion matrix is a tool that gives a further breakdown of the accuracy and an example for the Neural Network model is shown in Figure 27.

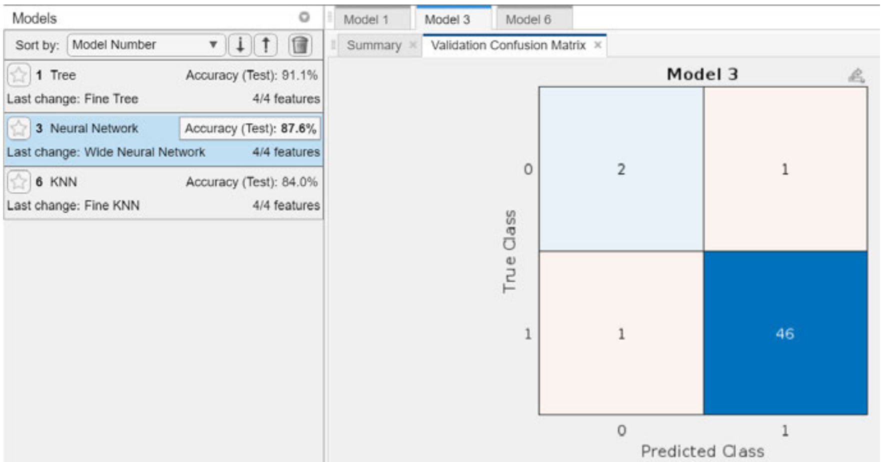

Figure 27: validation confusion matrix using training set of 50

The matrix tells me that the model has been trained such that on only two occasions does the model disagree with the supplied training data. The model now requires testing.

When originally organising the data a random set of 10,000 was set aside for model testing. When the test was completed the accuracy of the model was more exposed with approximately 1200 cases of incorrect predictions (more than 10% of the test data).

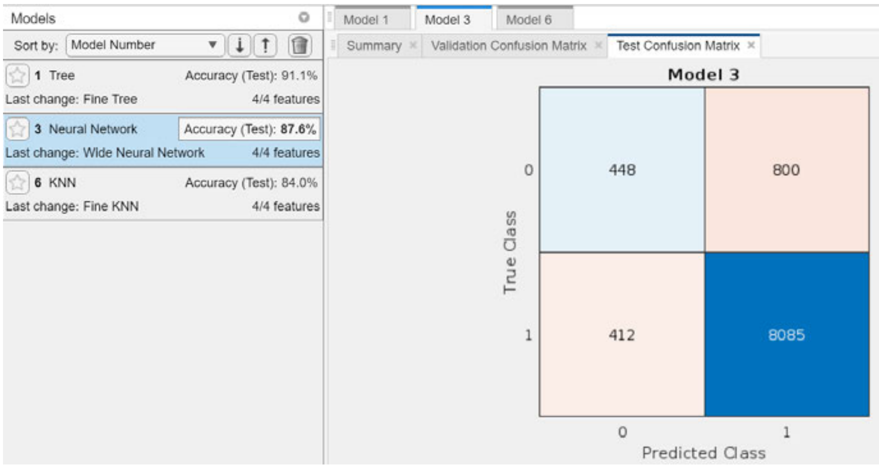

Figure 28: confusion matrix using training set of 50 and test set of 10,000

The other model performance test performed is the receiver operating characteristic (ROC) curve which dates from World War II when it was used for analysis of radar signals. It is still used as an intuitive tool for comparing the effectiveness of different classifiers. An area under curve (AUC) of 1.0 would be a high-performance model. In the case of the original model, built from 50 samples, the AUC score of 0.68 indicates this is not an effective model (Figure 29).

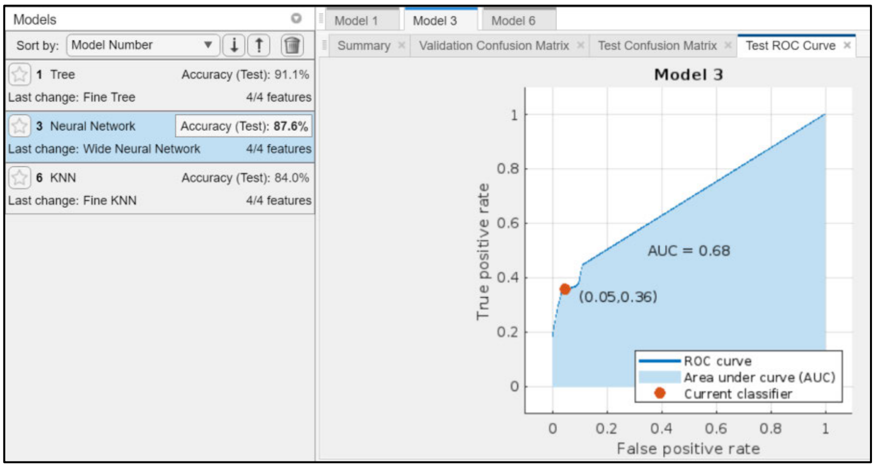

Figure 29: ROC curve using training set of 50 and test set of 10,000

5.4 Iterate the model

When organising the data earlier in this section it was conveyed that training data of approximately 40,000 sets was available. Using only 50 of these sets in the first model iteration was deliberately done so that model accuracy could be recorded as training data sets increased.

Training data sets were subsequently applied to models with increasing set numbers of 500, 5000 and 40,000. The same data set of 10,000 was used on all of these models. Results of increasing accuracy with training volume are shown in Figure 30.

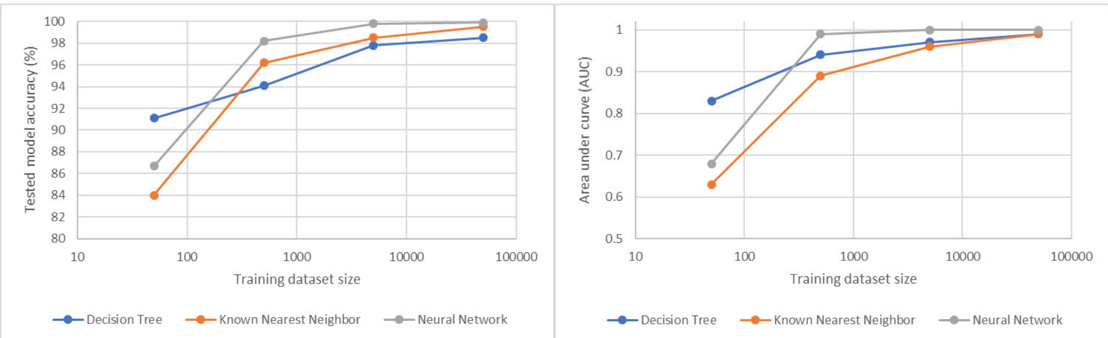

Figure 30: Data accuracy graphs as training set volume increases

The Neural Network model was shown to give the most accurate model but the Known Nearest Neighbor also showed the benefits of increasing points of reference. The Confusion Matrix and ROC curve for the most accurate model are given in Figure 31 and 32.

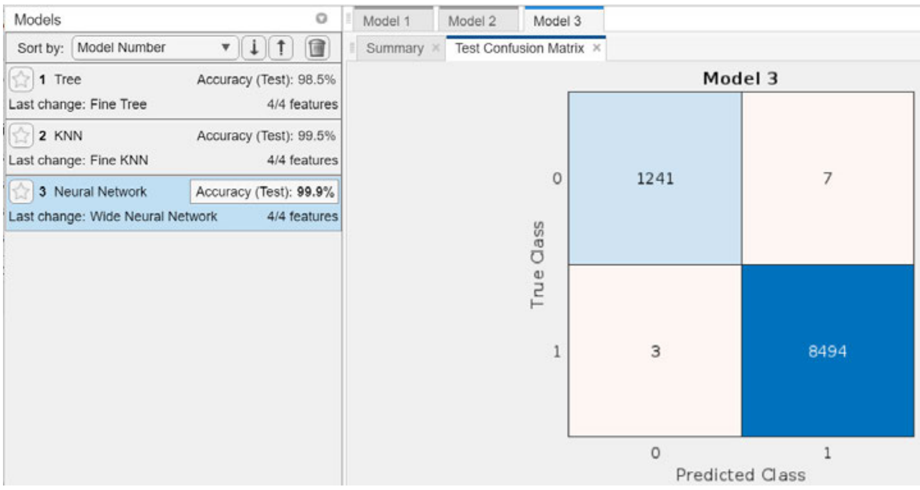

Figure 31: confusion matrix using training set of 40,000 and test set of 10,000

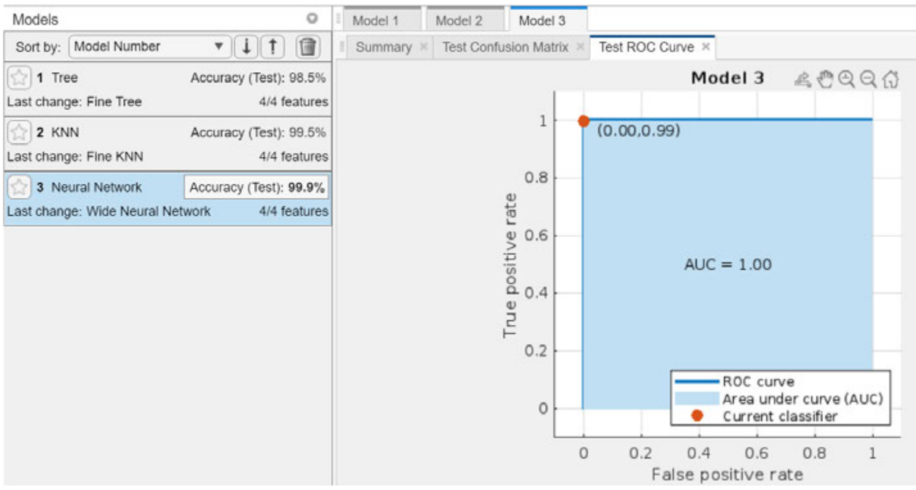

Figure 32: ROC curve using training set of 40,000 and test set of 10,000

With an accurate model at hand it was then exported into Matlab (Figure 33) where any new set of variables could be directly evaluated.

Main_test.m

```
clear;clc;close all
load modelwidenn.mat % Load the model you trained and saved
%load test_data.mat % Load new data for test
test_data=xlsread('overload2022_07_20.xlsx',1,'A1:D1');
test_input=test_data(:,1:4); % inputs of test data
test_label=test_data(:,end); % real label of test data
[Prediction_result,scores]=trainedModel1.predictFcn(test_input);

for i=1:length(test_label)
    if test_label(i)==0
        T_test_label(i)=categorical({'Over Load'});
    else
        T_test_label(i)=categorical({'Normal Load'});
    end
```

Figure 33: trained model used in Matlab directly on new data

During the course of the project an actual overload occurred on a wagon traversing the network and this caused business interruption while it was removed. Notwithstanding there are assumptions and limitations of this project work, but as far as bending moment applied on 6m spans goes, the model states that this overload, when considered with the associated key variables, was not a bridge overload (Figure 34).

Figure 1 | overload2022_07_20.xlsx

	A	B	C	D
	Var1	**Var2**	**Var3**	**Var4**
	Number	Number	Number	Number
1	**21.9**	**1790**	**16.2**	**3180**

Figure 34: real 15% overload axle tested on model

6 Discussion

6.1 Overall findings

An accurate machine learning model was successfully created to evaluate if a bending moment threshold has been exceeded by any combination of loads and spacings. The Neural Network classification learner model was found to be 99.9% accurate, given sufficient training data. The volume of training data required to see high accuracy was approximately 5,000 sets.

The hypothesis that an axle overload does not represent a span overload was proven and, in many circumstances, an axle overload within a group imparted less bending moment than regular loads at closer spacings. This idea is not a new finding and simple static analysis could demonstrate this clearly. The finding is that a machine learning model can successfully be trained to immediately evaluate and confirm this hypothesis.

6.2 Limitation of results

One of the simplifications required to develop the analytical training model was to assume a bending moment maximum value at midspan. This was validated during the project development by a sophisticated analytical model (Cognos) where negligible error was found when spacing and load variables were respectively similar. A validation is now made on the model where load and spacing variables are quite distinct from each other. The actual overload in Figure 34 was such a scenario. This load is visually represented in Figure 35.

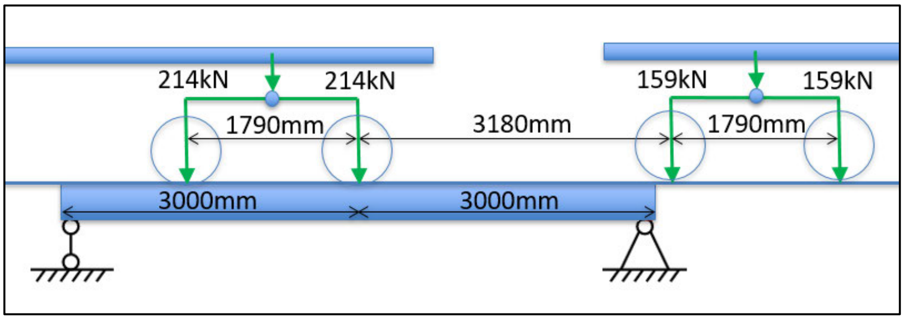

Figure 35: training model axle position assumption for maximum bending moment calculation

The midspan bending moment when one of the heavy axles was at midspan was evaluated as 452.2 kN.m using the Excel analytical training model. At 98% of the reference bending moment of 466.4 kN.m the machine learning model rightly confirmed this as an 'ok' set of axles. An engineer, by observation, would examine Figure 35 and estimate that the maximum moment will be when the two heavy axles are centrally located. When checked using the Cognos model, which incrementally evaluates bending moment across the span, the result confirms this and shows the training model is non-conservative in this scenario.

Span Length	E40 Moment (kNm)	Vehicle Moment (kNM)	E. Vehicle Moment	E40 Shear (kN)	Vehicle Shear (kN)	E. Vehicle Shear
5.5	463.62	412.55	35.6	416.84	373.67	35.9
6.0	544.01	464.75	34.2	441.44	391.45	35.5
6.5	631.60	517.16	32.8	462.25	406.49	35.2
7.0	719.56	569.71	31.7	480.09	424.84	35.4

Figure 36: real 15% overload axle tested on Cognos application

The error from the project assumption that the maximum bending moment occurs at midspan when an axle is also at midspan can therefore be estimated as up to 3% non-conservative. This error value is based on the analytical model bending moment (452.5 kN.m) and the more accurate Cognos-sourced bending moment (465.75 kN.m).

The second limitation is that bending moment only was used as the stress of choice in this study but shear force is also a significant consideration which has not been evaluated.

The focus span length of 6m proved to be a good sample size to develop a model using four input variables but the spans on the network that the load may traverse range from 1.5m to 75m. To have a model that gives full coverage of the network there are perhaps 90 variations required.

Span Length	Vehicle Moment (kNM)	Vehicle Shear (kN)	Span Length	Vehicle Moment (kNM)	Vehicle Shear (kN)	Span Length	Vehicle Moment (kNM)	Vehicle Shear (kN)
1.5			8.0			26.0		
1.8			9.0			28.0		
2.0			10.0			30.0		
2.3			11.0			32.0		
2.5			12.0			34.0		
2.8			13.0			36.0		
3.0			14.0			38.0		
3.5			15.0			40.0		
4.0			16.0			45.0		
4.5			17.0			50.0		
5.0			18.0			55.0		
5.5			19.0			60.0		
6.0			20.0			65.0		
6.5			22.0			70.0		
7.0			24.0			75.0		

Figure 37: green cell showing machine learning model limitation

As the span length studied increases more axles will load the span concurrently. This will increase the variables which may reduce the accuracy of models on longer spans. The Excel analytical model developed for this project is limited to considering four axles only.

The final limitation to note is that the study is still an offline assessment. Data was manually exported from the weigh-in-motion sites, preprocessed into variable sets and then run through the trained model. These are essentially steps 8 & 9 from the current overload process, repeated below in Figure 38.

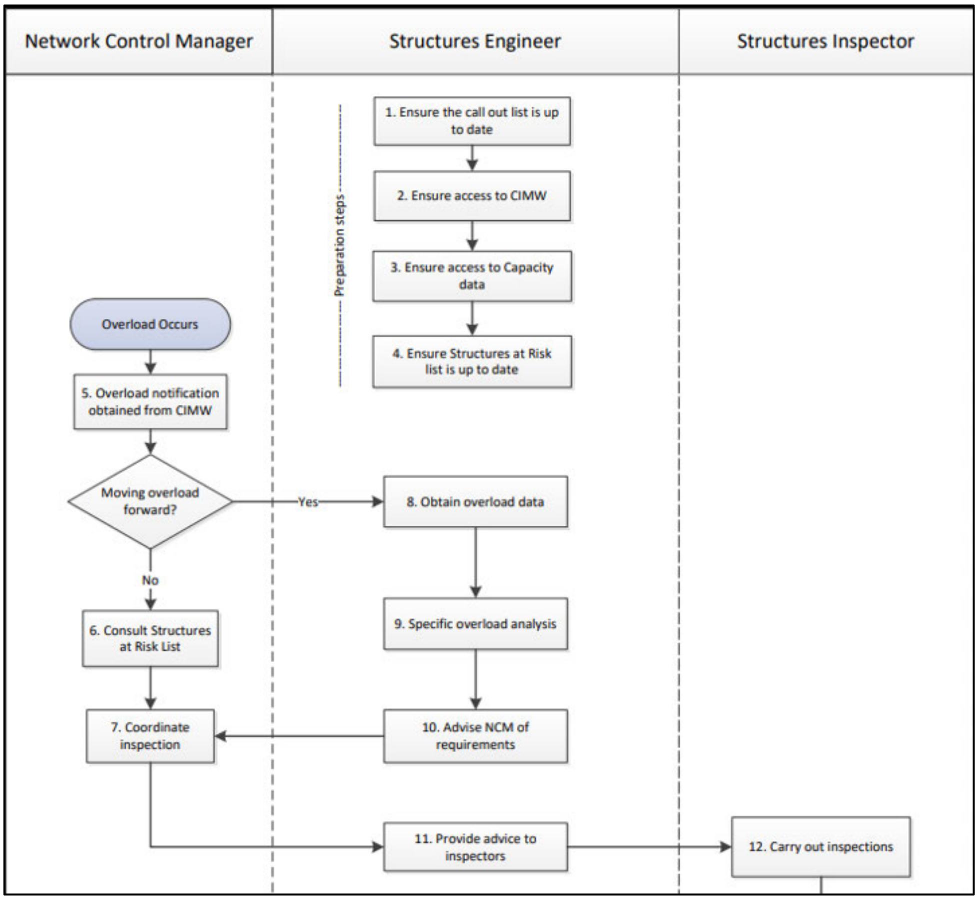

Figure 38: Initial part of structural evaluation of overload process

To reap the operational benefits and achieve a reduction in railway line closure following individual train axle overload the model would need to intercept the weigh-in-motion data and undertake evaluation before a determination of structural overload is given.

7 Conclusion

7.1 Project Achievements

The objectives of this project were to:

- develop an analytical training model for axle load assessment, and
- train a machine learning model for axle load assessment.

An analytical training model was created to evaluate bending moment due to various load and spacings across a 6 m span. The analytical model was evaluated as having an error of up to 3% non-conservative due to some assumptions made for simplification purposes.

The classification learner application was used to develop a model with the analytical model output used for supervised learning and model testing. A highly accurate model was successfully established once the training data volume got to approximately 5,000 sets.

7.2 Future Work

Data consisting of axle loads and spacings between these loads are available in large quantity. This project has shown how a machine learning model can be trained to improve the categorisation of a single axle structure overload alert by considering the associated axle grouping over a considered span length.

Some future work avenues that could be explored to continue to evaluate opportunities are:

- Make an improved analytical training model. The model doesn't particularly have to use the weigh-in-motion data for the training aspect. So long as a well-considered range in expected variables is used then it could be produced in any moving load analysis tool.
- Evaluate a machine learning model accuracy over a wider range of span lengths and

include shear force.

- Putting machine learning aside, an analytical model could be programmed to undertake moving load analysis directly following the passage of a train.
- Integration with weigh-in-motion suppliers to improve their customer offering by giving added value to the information output. Even if overloads may not be an issue perhaps there is merit in this with regard to less conservative fatigue load cycle accumulation. Cycles can be accumulated based on real data rather than characteristic trains. Fatigue life extension could be a benefit.

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Appendix A: Project specification

ENG4111/4112 Research Project

Project Specification

For: Michael Keenan

Title: Using weigh-in-motion data and machine learning for rail bridge load assessment

Major: Civil

Supervisors: Andy Nguyen (USQ) and Yang Yu (external supervisor)

Confidentiality: Use of KiwiRail Weigh-in-Motion Data will require approval.

Enrollment: ENG4111 – EXT S1, 2022

ENG4112 – EXT S2, 2022

Project Aim: Establish if a machine learning model can be effective for this type of application.

Programme: Version 1, 12th March 2022

1. Conduct literature research on CWIM, rail bridge loading and machine learning application in engineering context.
2. Narrow down focus area and establish aim of project.
3. Develop analytical load evaluation model.
4. Develop machine learning model.
5. Assess machine learning effectiveness for assessing overloads.
6. Evaluate results.
7. Write the report.

If time and resource permit:

8. Validate the developed model with a larger dataset.
9. Assess integration of analytical and machine learning model for decision making in this type of application.

Appendix B: Risk register

Safety Risk Management Plan – Offline Version			
Assessment Title:	Machine learning research project	Assessment Date:	16/05/2022
Workplace (Division/Faculty/Section):	University of Southern Queensland	Review Date:(5 Years Max)	16/08/2022
Context			
Description:			
What is the task/event/purchase/project/procedure?	Conducting a research project		
Why is it being conducted?	To increase body of knowledge regarding machine learning in a moving force environment		
Where is it being conducted?	In a home office environment and on a train while commuting to work		
Course code (if applicable)	ENG4111/4112	Chemical name (if applicable)	
What other nominal conditions?			
Personnel involved	Mike Keenan		
Equipment	Computer		
Environment	Inside office setting and on a train		
Other			
Briefly explain the procedure/process	gather data from weigh-in-motion sites and evaluate the use of a machine learning moelde to assess the data		
Assessment Team - who is conducting the assessment?			
Assessor(s)	Dr Andy Nguyen		
Others consulted:			

Eg 1. Enter Consequence

Eg 2. Enter Probability

Eg 3. Find Action

	Consequence				
Probability	**Insignificant** No Injury 0-$5K	**Minor** First Aid $5K-$50K	**Moderate** Med Treatment $50K-$100K	**Major** Serious Injuries $100K-$250K	**Catastrophic** Death More than $250K
Almost Certain 1 in 2	M	H	E	E	E
Likely 1 in 100	M	H	H	E	E
Possible 1 in 1000	L	M	H	H	H
Unlikely 1 in 10 000	L	L	M	M	M
Rare 1 in 1 000 000	L	L	L	L	L
Recommended Action Guide					
E=Extreme Risk – Task ***MUST NOT*** proceed					
H=High Risk – Special Procedures Required (See USQSafe)					
M=Moderate Risk – Risk Management Plan/Work Method Statement Required					
L=Low Risk – Use Routine Procedures					

Step 1 (cont)	Step 2	Step 2a	Step 2b	Step 3			Step 4				
Hazards: From step 1 or more if identified	***The Risk:*** What can happen if exposed to the hazard without existing controls in place?	***Consequence:*** What is the harm that can be caused by the hazard without existing controls in place?	***Existing Controls:*** What are the existing controls that are already in place?	***Risk Assessment:*** Consequence x Probability = Risk Level			***Additional controls:*** Enter additional controls if required to reduce the risk level	***Risk assessment with additional controls:***			
				Probability	**Risk Level**	**ALARP? Yes/no**		**Consequence**	**Probability**	**Risk Level**	**ALARP? Yes/no**
Example											
Working in temperatures over 35° C	Heat stress/heat stroke/exhaustion leading to serious personal injury/death	catastrophic	Regular breaks, chilled water available, loose clothing, fatigue management policy.	possible	high	No	temporary shade shelters, essential tasks only, close supervision, buddy system	catastrophic	unlikely	mod	Yes
Neck Injury	long term neck pain from incorrect posture in front of laptop on train	Minor	regular breaks,	Possible	Moderate	No	stretches,	Minor	Unlikely	Low	No
Stress	Work, family, study demands effecting physical and mental health	Moderate	Discuss commitments with family, work manager and study supervisor to agree expectations.	Possible	High	No	Focus more on planning	Moderate	Unlikely	Moderate	No

Step 5 - Action Plan (for controls not already in place)			
Additional controls:	*Resources:*	*Persons responsible:*	*Proposed implementation date:*
Learn some effective neck Stretches	Internet	Mike Keenan	30/05/2022
			Click here to enter a date.