NTNU
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Bridge Weigh-in-Motion System for Steel Railway Bridges

Implementation, development and analysis

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Abstract

This master thesis seeks to develop a BWIM system by using the programming environment Matlab, based on existing Bridge Weigh-in-Motion systems and the founding theories behind it. The developement uses a beam model to create a strain signal based on it's properties and moment influence line. The beam model is subjected to moving loads representing train axles, which induces strain at a sensor placed arbitrarily along the beam. To use as realistic a signal as possible through this model, white gaussian noise and dynamic effects are included in the signal. The resulting signal is used to develope and validate the BWIM algorithm. When the methods for finding speed and axle distances was within a decent level of accuracy, the developement of a linear matrix method for finding the influence lines was the next phase. This was based on the properties of the train inducing the signal and the signal itself. This thesis shows how the different elements of a BWIM program can be solved programaticly.

The thesis' empirical data was collected from Leirelva railway bridge, where a setup of strain gauges measured the bridge response for in all 6 different trains. This data was then used to analyse how a BWIM system would perform for this typical early 1900's Norwegian steel railway bridge. Identifying the passing trains velocities proved to be of particular importance to the BWIM system. The velocities of the trains were found through a brute force method. The matrix method proved to perform well for all the different signals, creating a influence line capable of nearly recreating the original signal, given the speed, and axle distances and weight. However, since the actual train weights was unattainable it was not possible to control the identified influence lines by using them to calculate the axle weights for comparison. The final influence lines used for calculation of axle weights, was obtained by averaging the results for the different train passages and a final filtering to rid the resulting influence line of unwanted noise.

This thesis highlights the difficulties of developing a BWIM system. By analysing how it performed for the data material from Leirelva bridge, the thesis shows that a BWIM system likely will work for these types of bridges.

The source code of this thesis will be made available on https://github.com/torholmslette-bak/master2016

Sammendrag

Denne masteroppgava søker å utvikle et 'Bridge Weigh-in-Motion-system' gjennom programmeringsmiljøet Matlab, ved å ta utgangspunkt i eksisterende BWIM-systemer og de grunnleggende teoriene bak. Gjennom utviklingen av BWIM-systemet benyttes en bjelkemodell for å lage et tøyningssignal, basert på modellens egenskaper og momentinfluenslinje. Bjelkemodellen blir utsatt for bevegelige laster som representerer togaksler. Lastene induserer tøyning i en sensor som er plassert vilkårlig langs bjelkemodellen. For å bruke et så realistisk signal som mulig, har hvit gaussisk støy og dynamiske effekter blitt inkludert i signalet. Det resulterende signalet inkludert effekter brukes til å utvikle og validere BWIM-algoritmen. Når metodene for å finne hastigheten og akslingsavstanden til lastene ble funnet å være innenfor god nøyaktighet, ble neste trinn å utvikle en lineær matrisemetode for å finne influenselinjene. Matrisemetoden tar i bruk togets vekt, fart og akselavstand, og signalet selv. Denne masteroppgava viser hvordan ulike elementer av et BWIM program kan løses programmatisk.

Masteroppgavas empiriske data har blitt samlet fra Lerelva jernbanebru, hvor utplasserte tøyningssensorer målte responsen av seks ulike tog. Disse dataene ble deretter brukt til å analysere hvordan BWIM-systemet fungerer for denne typiske tidlig 1900-talls norske jernbanebrua i stål. Å finne hastigheten til passerende tog viste seg å være av stor viktighet for BWIM-systemet. Togenes hastighet ble funnet gjennom en 'brute force' metode. Matrisemetoden viste seg å fungere bra for de ulike signalene, gitt gode estimater av togets hastighet, akselsavstand og akselsvekt. Siden de faktiske akselvektene til togene ikke er kjent, kunne ikke akselvektene som er beregnet gjennom de kalkulerte influenslinjene bli kontrollert ved sammenligning av faktiske verdier. De endelige influenslinjene brukt til beregningen av akselvekter, ble funnet ved å ta gjennomsnittet av resultatene for de ulike togpasseringene og en endelig filtrering av uønsket støy.

Masteroppgava framhever vanskelighetene ved utviklingen av et BWIM-system. Gjennom å analysere hvordan systemet fungerte for datamaterialet fra Lerelva bru, viser oppgava at et BWIM-system har gode forutsetninger for å fungere for denne brutypen.

Kildekoden brukt i masteroppgava vil bli gjort tilgjengelig via https://github.com/torholm-slettebak/master2016

Preface

This semester I got the opportunity to work with my favourite type of construction - bridges. I got to implement a system capable of weighing a train while it passes a bridge. This has been a major challenge including an infinite number of bugs and other problems. To actually be part of, and hopefully contribute to, a very interesting and limitless technology has perhaps been the highlight of my time spent at NTNU.

I would like to thank Anders Rønnquist, Gunnstein Thomas Frøseth and Daniel Cantero Lauer for the oportunity to work with BWIM, as well as their valuable input and many hours of help to a student sometimes lost within the world of BWIM.

Also major thanks to my Silje, who contributed with several cups of coffe and a keen eye for spotting errors in my sometimes rubbish writing.

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1. Introduction

1.1 Background

The Norwegian railway network covers large distances of Norway where sea, mountains and rivers causes the need of a large number of bridges. There are over 3000 railway bridges in Norway [11], many of which were built in the period 1900 - 1950. This means that many bridges are around 100 years old and are closing in on their designed lifespan, and are built with old methods and steel. The railway is in constant evolution, and over time the train velocities has increased as well as traffic density. With lifespans of around 100 years, a steel railway bridge needs properties to withstand weather and continous loading. This means continous inspections of bridges are required. Every sixth year Norwegian bridges are subject of a major inspection, for uncovering corrotion, and other damages of fatigue. This is a process demanding time, resources and manpower. Therefore good estimates of traffic impact on older and newer bridges are a necessity.

Bridge weigh-in-motion (BWIM) technologies was first developed in the USA in 1978. The initial system consisted of strain sensors placed beneath the bridge and sensors beneath the road, but systems using only strain sensors also exists. The general principle of a BWIM system is that a vehicle's axles induce strain in the bridge proportional to the influence ordinate and the magnitude of axle load. Thus from knowing the influence line for a sensor location and the measured strain, the axle weights can be calculated. In both road traffic and railway, static scales have been, and still are, used to determine a vehicle or trains weight. The static nature of such a system requires that the vehicle stands still, which limits traffic flow and causes general inconvenience for both people performing the weighing and the drivers occupying the vehicles. Bridge weigh-in-motion gives the abilty to determine traffic flow over a bridge and the ability to monitor weight of trains, and thus to detect possible overloading of trains. The BWIM system can be implemented so that it provides a continous data flow and automatic detection of trains and calculations of axle weights. This would provide information of bridge behaviour for different types of trains, different loads, and weather conditions. It will also provide data describing dynamic effects on the bridge. This data could be used to find the optimal crossing velocities for different train types. A permanent BWIM system providing continuous data could measure changes of bridge property over time, making it a bridge health monitor. Changes in the bridge could be detected without a major inspection. A BWIM system could in theory detect internal changes of a bridge, which could go undetected by a visual inspection. BWIM traffic data including vehicle loads and traffic density can be combined with degradation data to estimate how traffic density affects the aging of a bridge. It can over time provide us with estimates of what demands future bridges spanning similar crossings will be subjected to.

BWIM systems have in general been used for road bridges, and different versions of BWIM is used in Europa, USA and Australia. For railway bridges this is not the case, according to González, [1] only Liljencranz's [5] and one other implementation of BWIM for railwaybridges have been made. Compared to road traffic, a railway bridge has constant properties making it suitable for BWIM. The trains always follow the same track on a single track bridge, thus a BWIM railway system doesn't need to make special considerations for transversal effects varying from train to train. Also, with a single track rail, the BWIM system doesn't need to account for multiple vehicle events. On the other hand, it requires capabilities to deal with a large number of axles, and long strain signals.

1.2 Research objectives

The main goal of this master thesis is to develope and investigate methods of calculating influence lines for steel railway bridges. A working method for calculating influence lines will enable a BWIM system to be installed on any bridge without having to build a full CAD or frame model. A direct calculation of influence lines by hand for an existing bridge is possible, but this is something which will entail a lot of work, and because of degradation of bridges it might be difficult to correctly determine it's properties. Since the influence lines for a bridge are difficult to derive by hand, one of my goals for this thesis is to further develope and test the algorithm from the Matrix method. Influence lines are one of the main foundations in BWIM. To accomplish calculating influence lines, I will develope my own version of a BWIM program. This thesis will focus on a system independent of axle detectors, using only the strain gauges placed on a bridge to perform BWIM. To do this, I have chosen the script language Matlab which well adapted for this thesis' puroses because of it's extensive math libraries, plotting abilities, toolboxes and simplicity which suits an early developement phase.
The goals of this master thesis:

1. Implement a working BWIM system
2. Implement methods for calculating the influence lines for an arbitrary bridge.
3. Identify good practices for building a BWIM system.
4. Analyse how Bridge weigh-in-motion works for a typical Norwegian steel railway bridge, through measurement data from Lerelva bridge.

2. Theory

This chapter contains theory that is fundamental for the thesis. This includes mathematical theory, and description of methods that enables the implementation of my BWIM system.

2.1 Bridge Weigh-in-Motion

A Bridge weigh-in-motion system is based on measurements of a bridge's deformation. The BWIM system uses these measurements to calculate passing vehicles axle loads. There are different approaches to assembling such a system, but they typically consists of a strain gauge measuring the strain induced by passing vehicles, an axle detector used to find the vehicle speed, and spacing of axles and a computer or data storage device. An algorithm is then able to use the data gathered from the axle detector and strain gauge to calculate axle loads. This thesis will focus on a system independent of axle detectors, using only the strain gauges placed on a bridge to perform BWIM.

2.1.1 Moses' Algorithm

"Moses' algorithm is based on the fact that a moving load along a bridge will set up stresses in proportion to the product of the value of the influence line and the axle load magnitude. The influence line being defined as the bending moment at the point of measurement due to a unit axle load crossing the bridge" [13, p. 35]. Each individual girder's stress is related to moment:

$$\sigma_i = \frac{M_i}{W_i} \tag{2.1}$$

Expressing the moment in terms of strain gives

$$M_i = W_i \sigma_i = E W_i \varepsilon_i \tag{2.2}$$

Where:

σ_i = the stress in the i'th girder

M_i = the bendind moment in the i'th girder

W_i = the section modulus

E = The modulus of elasticity

ε_i = strain in the i'th girder

The sum of the individual girder moments is therefore:

$$M = \sum_{i=1}^{N} M_i = \sum_{i=1}^{N} EW_i\varepsilon_i = EW\sum_{i=1}^{N}\varepsilon_i \tag{2.3}$$

The sum of the girder strains is proportional to the gross bending moment. The total bending moment and the measured strain is thus directly related by EW. These constants can be calculated through the bridge's dimensions and material properties. However through measuring the effects of a known vehicle passing the bridge these constants can be derived.

Weigh in motion is an inverse type problem, the strain is measured and the cause of the strain is to be calculated. The theoretical bending moment corresponding to axle loads on the bridge at one strain sample, is given by:

$$M_k^T = \sum_{i=1}^{N} A_i I_{(k-C_i)} \tag{2.4}$$

$$C_i = (L_i \times f)/v \tag{2.5}$$

Where:

N = *the number of vehicle axles*

A_i = *the weight of axle i*

I_{k-C_i} = *the influence line ordinate for axle i at sample k*

L_i = *the distance between axle i and the first axle in meters*

C_i = *The number of strain samples corresponding to the axle distance* L_i

f = *the strain gauge's sampling frequency, in* Hz

2.2 Influence lines

A influence line can be defined as: *"A graph of a response function of a structure as a function of the position of a downward unit load moving across the structure [4]."* For a BWIM system this response function typically is the bending moment at the sensor location. The influence line can be found through assembling a model of the bridge in any CAD or frame-program. This would however take a lot of time, especially for more advanced bridges. Depending on the support of the bridge, the influence lines takes different theoretical forms, as seen in Figure 2.1. The true influence line for a bridge lie somewhere in between the simply supported and fixed version [12, p. 146].

Znidaric and Baumgärter [12], did a study on the effects of choice of influence line. This study shows errors up to 10% for a short 2 m bridge span, and errors of several hundred percent

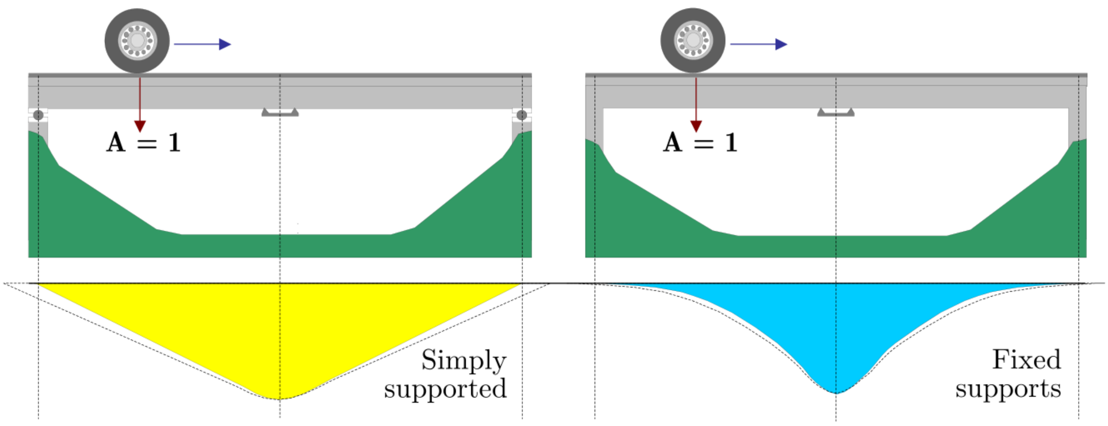


Figure 2.1: Influence lines for simply and fixed supported bridges, figure from [13]

for a 32 m bridge span, when using an incorrect influence line. This is illustrated by figure 2.2, showing how a veihicles gross weight is affected when the influence line is varied from a simply supported version to a fixed support version. This underlines the importance of using correct influence lines for a BWIM system.

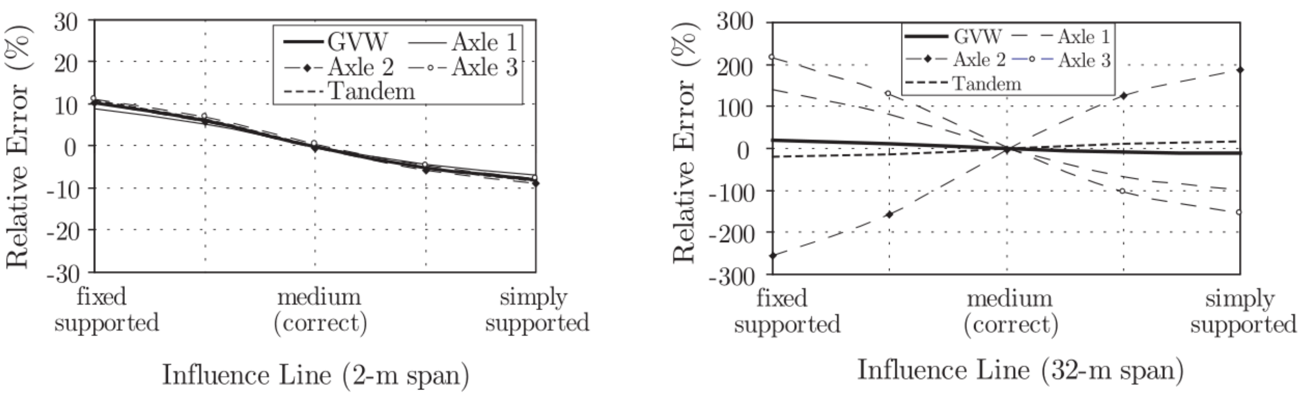


Figure 2.2: Errors of axle loads due to wrongly selected influence lines, figure from [13]

2.2.1 Using influence lines in the BWIM system

Even if a correct influence line for a BWIM setup is found, wrong placement of the influence line with respect to the strain signal is a major source of error. In theory it should be possible to detect the excact point of an axle passing over the sensor, as it results in a peak in the strain signal. This peak corresponds to the major peak in the influence line. A good example of this is seen in figure 2.3, which shows the influence line aligned with the strain signal from a 3 axle vehicle. The first peak of the strain signal corresponding to the the first axle of the vehicle should occur at the same location as the the peak of the influence line, which should be precisely at the sensor location. For closely spaced axles it may be difficult to detect the individual peaks, because they both influence the sensor at the same time, and because of system noise and dynamics.

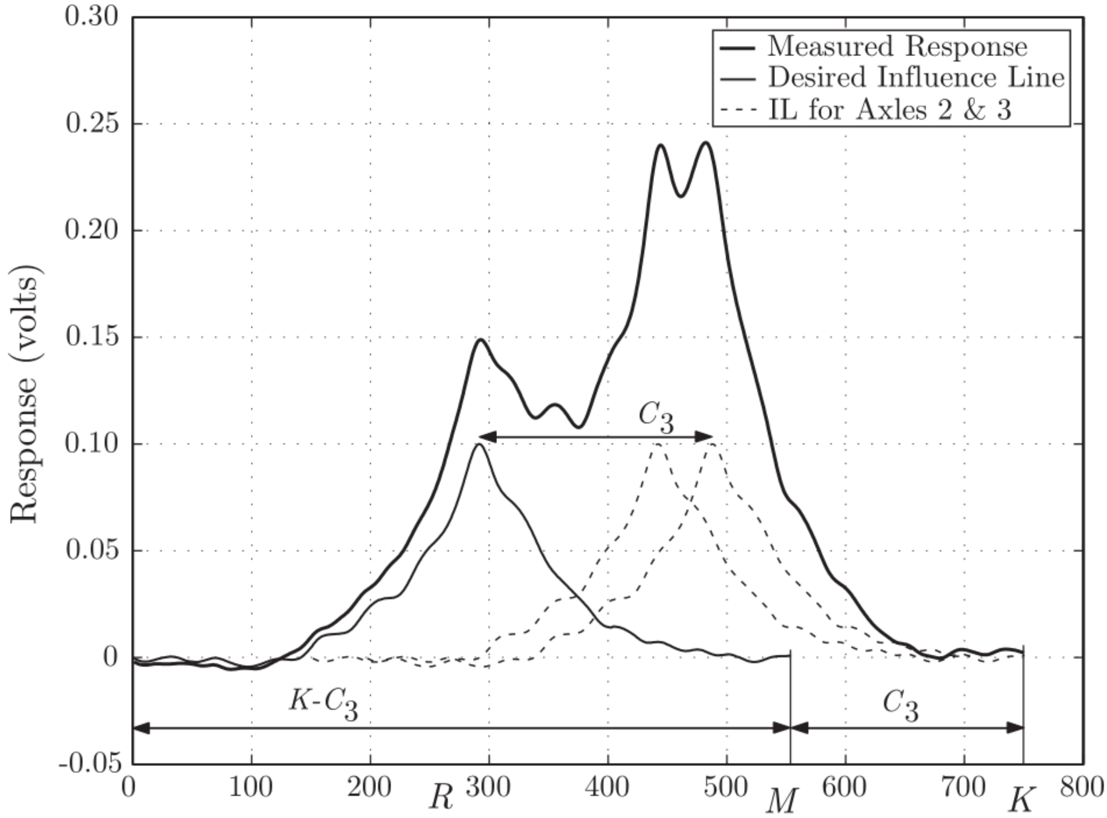


Figure 2.3: Placement of influence lines, influence line has been scaled.

2.2.2 Influence line through the Matrix Method

Quilligan [13] developed a Matrix method to calculate the influence line of a bridge through the measured strain induced by a vehicle. This method is derived from Moses', equation 2.6. The Matrix method calculates an influence line for a specific strain signal, given a known train with known axle weights and velocity. The found influence line is therefore subject to system noise and dynamics which are likely to vary from vehicle to vehicle. An averaging of a sufficient number of calculated influence lines should reduce the dynamic effects. The following description of the Matrix method is an extension of Quilligans thesis "Bridge Weigh-in Motion : Development of a 2-D multi-vehicle algorithm [13]", and shows the math for a general case with unlimited number of vehicle axles. In the appendix C, it is shown how the main part of the following description of the Matrix method has been implemented in Matlab.

$$Error = \sum_{k=1}^{K} [\varepsilon_k^{measured} - \varepsilon_k^{theoretical}]^2 \tag{2.6}$$

Equation 2.6 were originally used to filter out the dynamic response of the bridge. The theoretical strain in this equation can be expressed as a product of axle loads and influence ordinates at sampling points, see equation 2.4, thus we can expand equation 2.6:

$$Error = \sum_{k=1}^{K} \left[\varepsilon_k^{measured} - \Big(\sum_{i=1}^{N} A_i I_{(k-C_i)}\Big)\right]^2 \tag{2.7}$$

The set of influence ordinates I that minimizes $Error$, forms the wanted influence line.

$$\frac{\partial Error}{\partial I_R} = \frac{\partial \sum_{k=1}^{K} \left[\varepsilon_k^{measured} - \left(\sum_{i=1}^{N} A_i I_{(k-C_i)}\right)\right]^2}{\partial I_R} \tag{2.8}$$

For a given number of known axle loads this equation comes down to a set of $(K - C_n)$ number of linear equations. Rearranging the equations and writing them in matrix form leads to:

$$\left[Am\right]_{K-C_N,K-C_N} \left\{I\right\}_{K-C_N,1} = \left\{M\right\}_{K-C_N,1} \tag{2.9}$$

Where:

$\left\{M\right\}$ = a vector depending on axle weights and measured strain, $M_{i,1} = \left(\sum_{j=1}^{N} A_j \varepsilon_{(i+C_j)}\right)$

$\left[Am\right]$ is a matrix depending only on the axle loads, defined by equation 2.10.

$$\left[Am\right] = \sum_{i=1}^{N} \sum_{j=i}^{N} \left[Am\right] + \left(A_i A_j \left[D\right]_{C_j - C_i}\right) \tag{2.10}$$

Which produces the upper triangle of the symmetric $\left[Am\right]$ which through the transpose operation can be used to build the full matrix. Where:

$\left[D\right]_{C_j-C_i}$ = a matrix containing only one diagonal of ones, where the diagonal is placed with an offset, $C_j - C_i$, from the center matrix diagonal.

Solving equation 2.9 for the influence ordinate vector gives the influence line for the strain history. This can be done through inversion of the $\left\{Am\right\}$ (equation 2.10) so that $\left\{I\right\} = \left\{Am\right\}^{-1}$ or other numerical solutions like a Cholesky factorization. In this project this was done through Matlab's "\" operator [8]. When the influence line and the axle spacings are known, the axle weights can be calculated by solving

$$A = \left\{I\right\} \backslash \epsilon \tag{2.11}$$

2.3 Finding the train's speed

By identifying a peak representing the same axle in the strain signals for two different sensors. The time difference between two such peaks is the time the train uses to travel the distance between the two sensors. Given the known distance between the sensors, s, the velocity is given by $v = s/t$. Through doing cross correlation between two sensors strain signals. Cross correlation measures the similarity between two signals as a function of the lag. This can be used to identify the lag between two similar signals. The cross correlation of two signals has maximum value at the lag equal to the delay. The time delay is then a product of the sampling frequency and the lag in samples.

2.4 Filtering and noise

All signals are subjected to noise, which can be defined as

> "Unwanted disturbances superposed upon a useful signal that tend to obscure its information content" [14]

Noise in a BWIM system can be intrinsic noise, that is noise generated inside a system, and extrinsic noise which is noise generated outside the system. A train approaching the BWIM sensors may be a source of extrinsic noise. Performing Bridge weigh-in motion relies upon the information provided by the sensor signals. When finding the distances between axles, noise is a source of distortion which may increase error of found distance. It may also make it difficult for the program to detect the desired peaks in the signal which corresponds to the trains axles. Smoothing the signal may therefore be completely necessary for a BWIM system. During the developement of my version of BWIM for this thesis, several attempts on finding and using appropriate noise filters have been made. Matlab contains many such filter functions which can be used, such as a Butterworth and SGOLAY filters. These were both tested and partially used, but are not directly present in my final BWIM system. The Butterworth filter nevertheless, proved worthy for identifying signal peaks in the development fase.

2.4.1 Noise smoothing through fourier transformation

MathWorks Practical Introduction to Frequency-Domain Analysis, see [9], describes how frequency analysis can be done with Matlab:

> "Frequency-domain analysis shows how a signal's energy is distributed over a range of frequencies. A signal can be converted between the time and frequency domains with a pair of mathematical operators called a transform. An example of this is the Fourier transorm which decoposes a function into the sim of a number of sine wave frequency components. The 'spectrum' of frequency components is the frequency domain representation of the signal. The inverse Fourier transform converts the frequency domain function back to a time function."

Performing a fast fourier transformation in matlab on a vector signal, gives the oportunity to remove unwanted frequencies from the signal. When the signal is transformed into the frequency domain, setting all the frequencies above 30 Hz to zero and then transforming the signal back into the time domain would smooth a typical BWIM signal greatly. Figure 2.4 shows filtering of a strain signal where frequencies above 20 Hz have been eliminated.

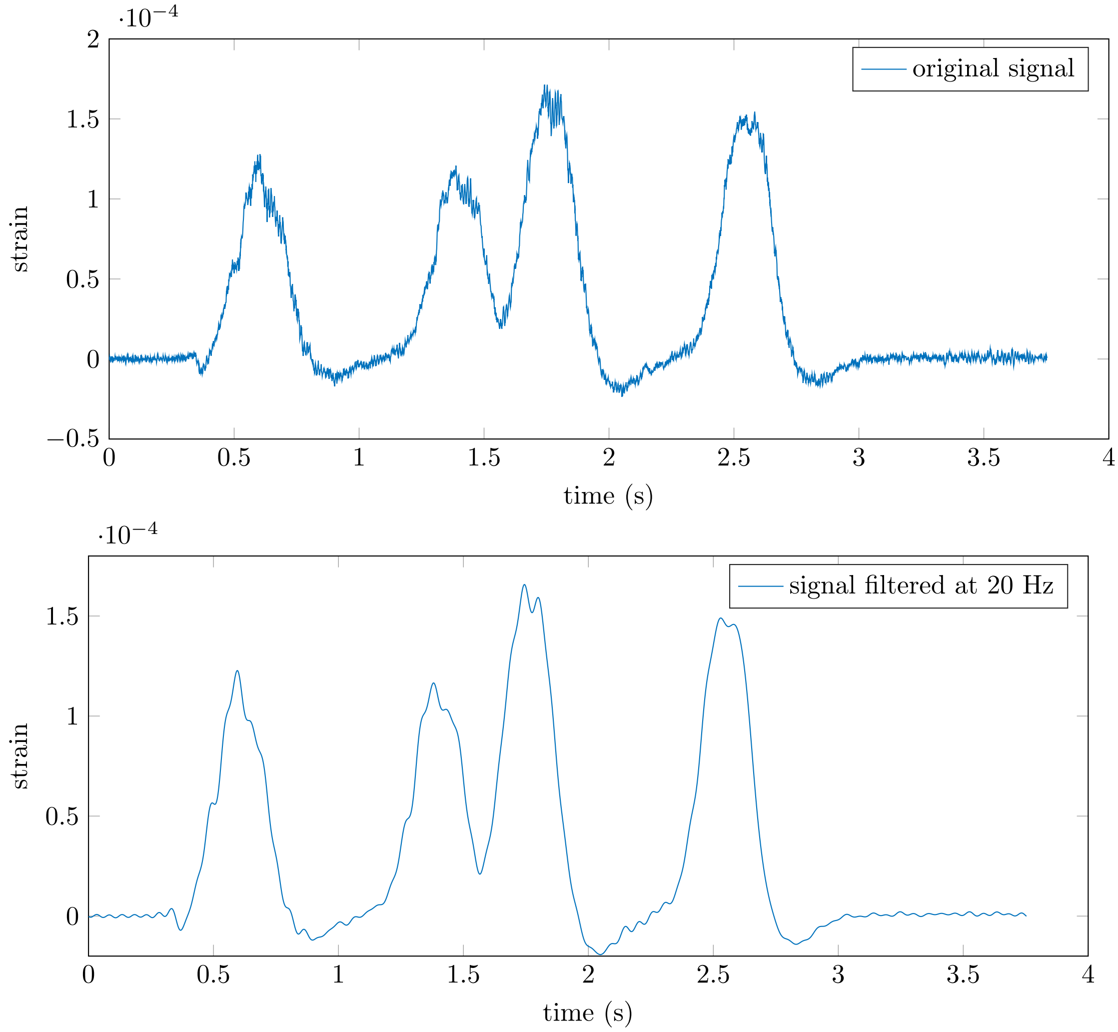


Figure 2.4: Figure showing filtering of a signal, where frequencies above 20 Hz in the signal have been eliminated

3. Method

This chapter describes the methods used in the thesis, and how the empirical data was obtained.

3.1 Programming a BWIM system

In the theory chapter we learned how a BWIM system works, the math behind it, and looking into how others have devloped such systems. This master thesis' goal is to create a working BWIM program. Matlab is chosen as the developement languague for the following reasons:

- Matlabs excellent plotting properties
- Simplicity
- Good tools for analysing and debugging the code
- Its large library of toolboxes and functions

Using Matlab [10], and wanting to make the BWIM program as simple and efficient as possible, I built a simple beam model of a bridge for simulating moving loads crossing it. The moving loads are crossing the longitudinal direction of the beam, simulating a passing train like shown in figure 3.1. The beam model was used to develope and validate the BWIM algorithm.

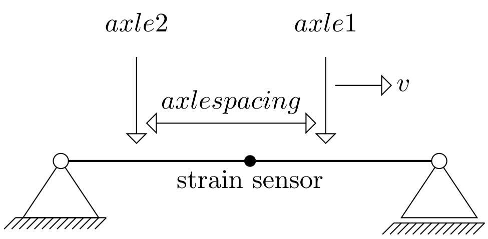


Figure 3.1: Beam model for developement of BWIM

A simple flow diagram describing the BWIM program:

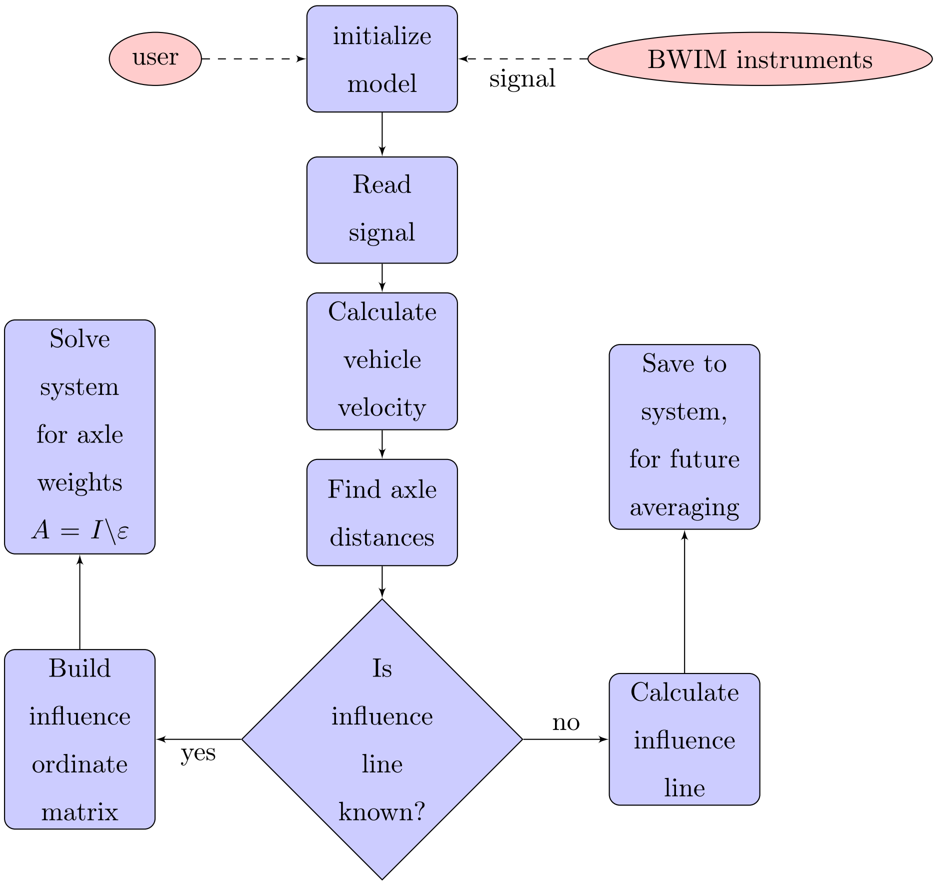


Figure 3.2: Flow chart describing a BWIM system

This flow chart shows the main parts of how my BWIM system is designed. Help functions solving small tasks for each box in the chart are excluded.

3.1.1 Producing a strain signal

Through the theoretical moment influence lines of the beam, a strain signal can be built through the moment-strain relationship, found in equation 2.3, for a given set of axle weights. A simple beam bridge model, as seen in figure 3.1, will not recreate a actual bridge strain signal but will be used to create a working BWIM system. The produced strain signal will differ from an actual strain signal mostly because of dynamics, from the train and bridge, and because actual boundary conditions of a bridge will differ from the boundary conditions of a simple beam model. The strain sensors will also produce noise distorting the signal. To make as good a signal as possible, some effort were placed into recreating the effect mentioned above. To add noise to the signal, white gaussian noise was included in the signal through Matlabs wgn function "http://se.mathworks.com/help/comm/ref/wgn.html". Such a produced signal can be seen in figure 3.3, which is produced by 8 axles moving across the bridge at 20 m/s.

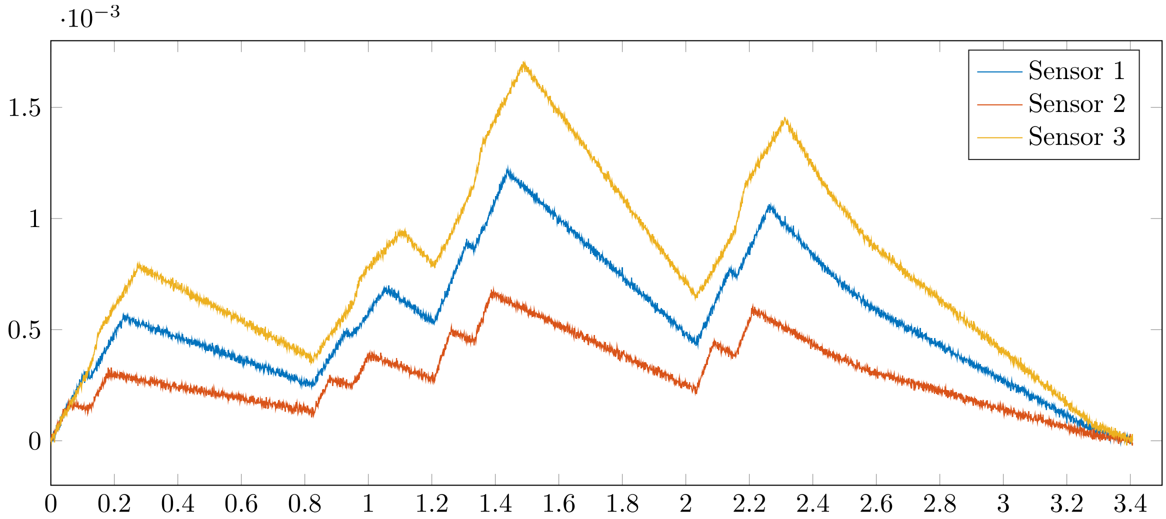


Figure 3.3: Strain signal created through beam model, sensor locations are as shown in sketch of the BWIM setup for Leirelva bridge 3.6

This theoretical strain signal will vary greatly from an actual strain signal measured on a bridge. The beam model used to develope this strain signal, may be comparable with simple bridge types like a single span slab bridge, but will not be comparable with more complex bridges. However for developing a BWIM program the simple beam model will suffice as the different modules of BWIM will be roughly the same no matter the bridge type.

3.2 System setup at Lerelva bridge

The Department of Structural Engineering had access to Lerelva bridge for test purposes, where we installed sensors using equipment on the underside of the bridge. Lerelva bridge is a typical Norwegian railway bridge built in 1921 and many similar bridges exists built in the same manner. It is a simple 25 meters steel truss bridge consisting of 5 verticals dividing the stringers into 6 sections. These stringers consist of angle profiles and plates built with the riveting teqnique. This bridge is of particular interest for a BWIM system because few or none have installed and tested such a system on a bridge of this type. If a BWIM system could be proved to work on one such bridge, it could easily be adapted to similar bridges. Based on construction drawings from around 1919 and especially B.1 and B.1, the dimensions of the bridge and sensor locations was determined and used as input for the BWIM program.

Empirical data for analyzing and developing the my BWIM system, was gathered by sensors under an actual bridge measuring train passings. The subject bridge is Lerelva bridge in Trondheim, figure 3.5, a typical Norwegian steel railway bridge. Three strain gauges, 3 mm 120 ohms from HBM, were placed by the support towards Trondheim on the first section of the longitudinal stringer, like shown in figure 3.4b and 3.6. The sensors were placed with 1 m spacing around the middle of the stringer section. These strain gauges were connected to a National

Instruments compactDAQ with module NI 9235 which produced an continuous data flow to a standard laptop, see figure 3.4a. A Kipor generator was brought for power.

(a) System setup from data gathering at Lerelva (b) Placement of strain gauges on stringer section

Figure 3.4: Instruments for aquiring strain data

Figure 3.5: Lerelva bridge with a train passing over

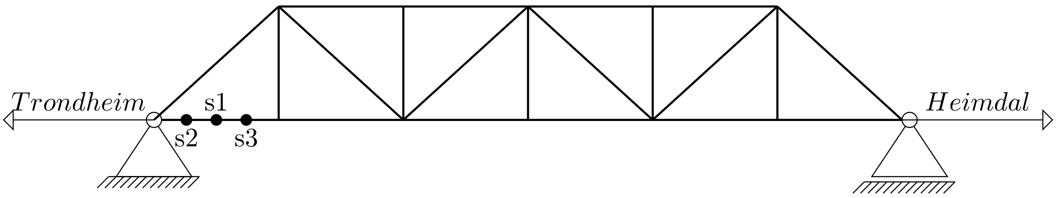


Figure 3.6: Sketch of bridge showing sensor locations for system setup at Leirelva bridge

3.3 Data gathered

The instruments discussed in 3.2, provides a measurement frequency of 1024 Hz. All data was gathered the same system setup during a single day. In all six trains were recorded passing the bridge. The system setup stored the signals for the three different sensors along with the time for the elapsed signals in a matrix for each train. The recordings of train passings were started and stopped manually, as no trigger was in place to start and end the signal automatically. Some of the gathered signals therefore ended up being very long, which means it requires to have essential data extracted. One of the reccordings was also very short, but still usable. Three of the trains we measured traveled towards Heimdal, and three towards Trondheim. For simplicity and necessity, this thesis assumes that the trains traversing Lerelva bridge does not accelerate or decelerate while influencing the sensor.

3.4 Trains

The trains passing the bridge were of two types, a short two vagon commuter of type NSB92 as seen in figure 3.7, and a freight train with a EL14 locomotive as seen in 3.8. The weight of the trains with passengers is unknown, resulting in axle weights being set equal the distibuted weight of the brutto train like shown in table 3.1 obtained from [2, p. 81]. For the freight train the properties of the locomotive was found through [3]. The axle distances was determined through figures 3.7 and 3.8.

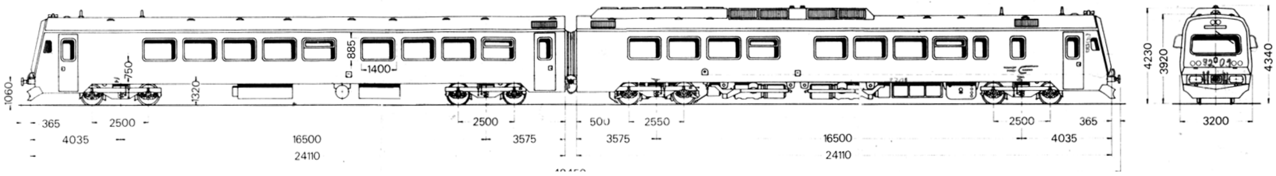


Figure 3.7: Axle distances of a NSB92 train

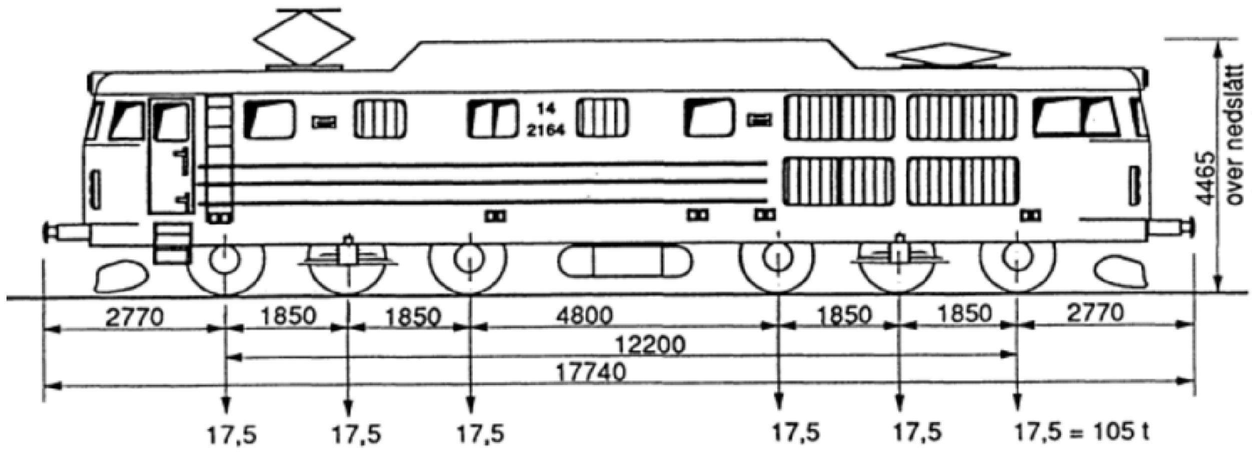


Figure 3.8: Axle distances and weights for a EL14 locomotive

Axle	1	2	3	4	5	6	7	8
Axle weight [kg]	9500	9500	9500	9500	14575	14575	14575	14575
sum	38000				58300			
sum total	96300							

Table 3.1: Table of axle weights used to calculate Influence lines

4. Analysis

This chapter will analyse the how my BWIM system performs, with special emphasis on the influence lines produced by the Matrix method. Sensor locations are as shown in figure 3.6, and are the source of the naming conventions in the plots in this chapter.

4.1 Strain data

The following figure 4.2, contains raw strain data for 6 different trains passing the Lerelva bridge. Each subfigure contains data from three different strain sensors placed as described in System setup, section 3.2. Three of the trains comes from the north side; train 3, train 5 and train 7, and three from the south side; train 4, 6 and 8. The strain signals all appear similar in form, except for train 7, figure 4.2e, which is a freight train. The other 5 trains are all of the same type, a NSB 92 type passenger train 3.7.

The strain signals have different levels of peak height suggesting that the trains actual axle weights differ from what is found in table 3.1. This will throw off the magnitude of the resulting average influence line found through the Matrix method. This error in calculated influence line will inevitably be found again in the calculated axle weights . To account for the different directions of the trains, the strain data for the trains going towards Trondheim has been reversed. This is not necessary for finding influence lines, but makes it easier placing the found influence lines in the same coordinate system. Some of the signals were originally very long, due to not knowing exactly when the train would pass. This means cutting the signal into a vector containing the essential data. Initially the goal was to identify exactly, or as closely as possible, the time the train entered the bridge. Due to noise and dynamic effects identifying this, proved a difficult process involving detection of peaks which lies close to peaks of noise. This proved possible to do for each individual signal, but a general method performing this for every signal was not within the authors capabilites. Therefore, to cut the signals as equally as possible the first and last major peaks of the signals were used as reference points for appending of samples before and after these peaks, as seen in figure 4.1. For this method to prove exact, the speed of the train should be taken into consideration when appending sample points so that the influence lines of the signals gets an as equal length as possible. The strain data from the freight train, figure 4.2e, is not used for finding the bridge's influence line because the train data is unknown.

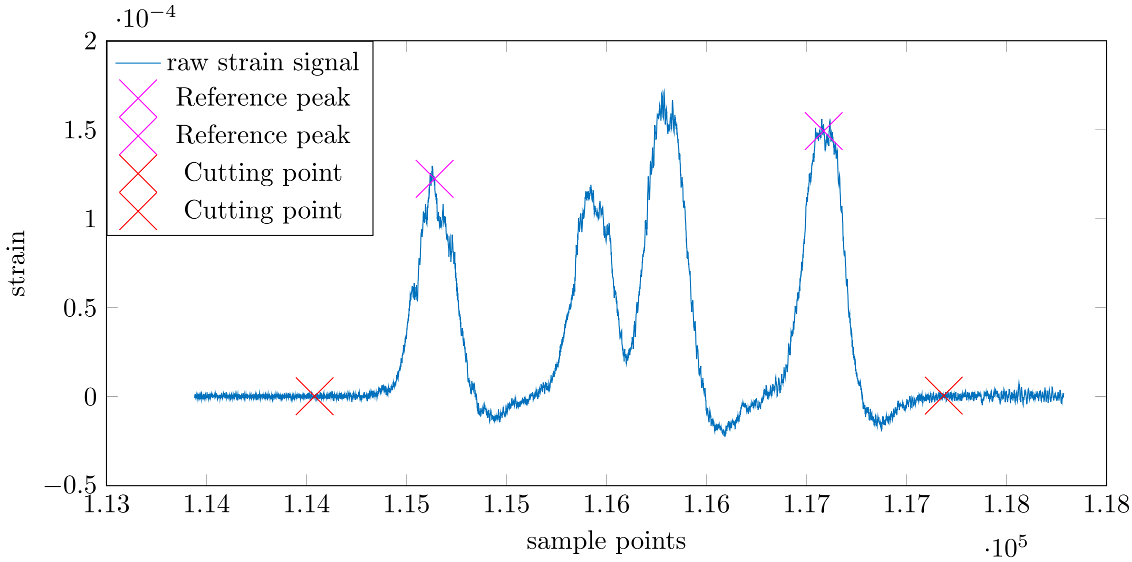


Figure 4.1: Plot showing the identified peaks and cutting points of strain signal

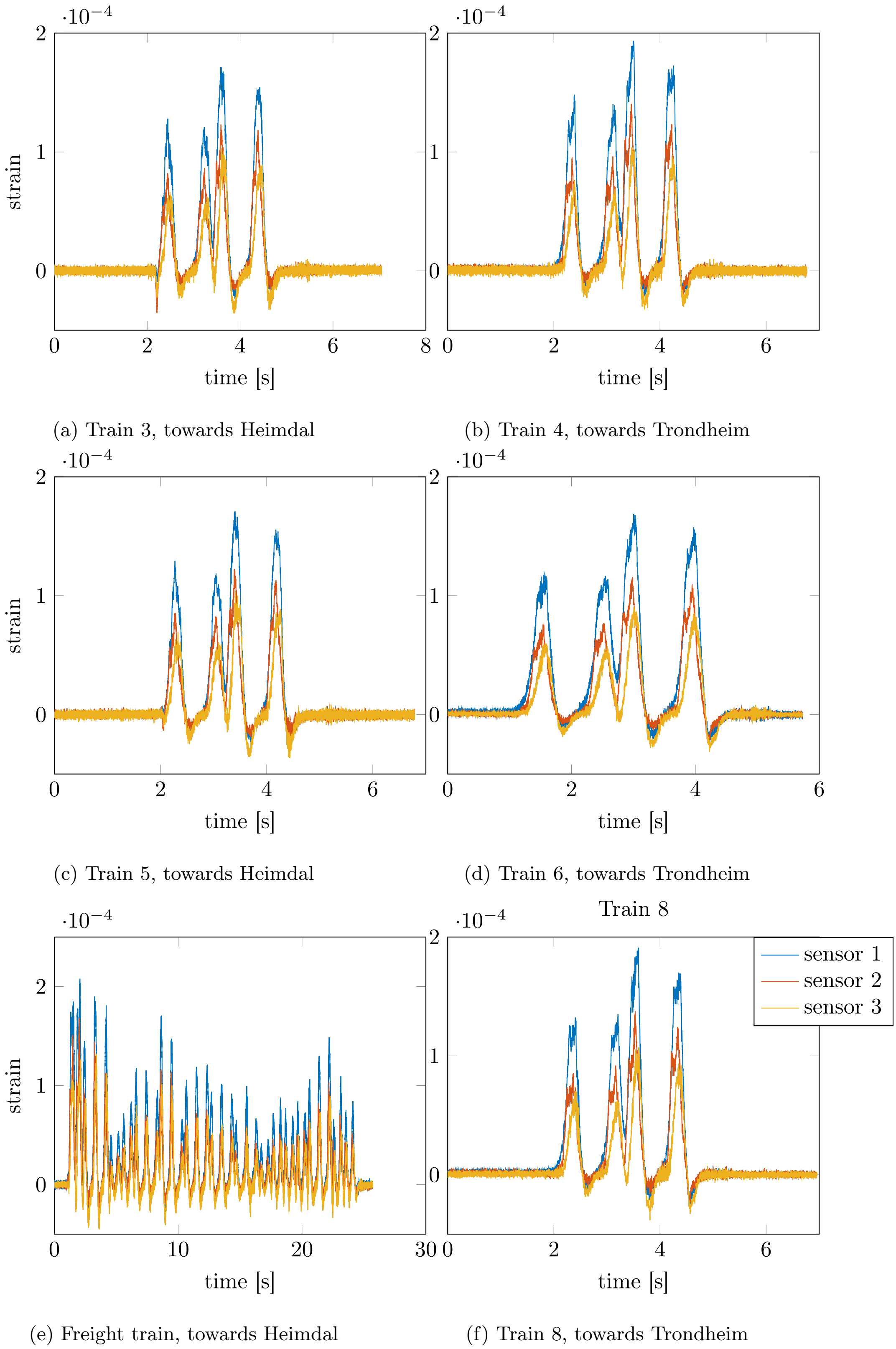
Axle weights for this train was not found, and guesswork of this data would be difficult. The properties of the freight trains locomotive is known, and as discussed in 4.8 this could in theory be used to calibrate thes sensors, and to identify errors in the BWIM system.

The numbering of trains originate from the numbering recorded signals. Some of the recorded signals did not contain information from a train passing resulting in the signals starting at train 3.

4.2 Finding the speed of the train

The importance of using the correct speed in a BWIM system becomes apparent when calculating influence line for a sensor. A wrongly determined speed will result in what looks like dynamic effects or an oscillating influence line, none of which should appear in a static influence line. If the influence line is known incorrect train velocities will still cause wrongly calculated axle weights. A correctly calculated speed is therefore of utmost importance for Bridge weigh-in-motion. As discussed in theory there are two ways used by existing BWIM systems to find the train's velocity. Both these methods have been implemented and tested, however they contained flaws making them unreliable, or unsuitable for this project.

- The method of **peak identification** 2.3, is very subjected to noise corrupting location of identified peaks. A train bogie typically consist of axles in pairs or threes, which will all influence the sensors simultaneously creating a major peak containing smaller peaks. In such a case the identification of a single peak can be difficult, and will likely provide faulty calculated velocity. Filtering was also employed by this method without being able to find general values of filtering. The filtering of the signal also distorted the peaks to a degree



(a) Train 3, towards Heimdal

(b) Train 4, towards Trondheim

(c) Train 5, towards Heimdal

(d) Train 6, towards Trondheim

(e) Freight train, towards Heimdal

(f) Train 8, towards Trondheim

Figure 4.2: Strain data from the three sensors of Leirelva bridge

where the result could be unreliable.

- The method of **phase difference** using cross correlation depends on strain signals where the trains velocities are known and the distance between two or more sensors. This method seems to work independently of noise which likely makes it superior to the peak method. This method will however require calibration for each setup of a BWIM system, due to the method needing a system constant depending on the bridge and the sensor placement. The velocity of the trains producing the strain signals in this thesis, was not known or attainable through NSB or Jernbaneverket and therefore this method were not applicable for finding velocities. Calibrating this method has neither been the focus of this thesis.

These two methods both work very well for a theoretical signal, however when noise and dynamics are introduced as well as more complicated bridge boundary conditions identifying the peaks representing the same axles becomes complex. A method identifying peaks, will have to adapt to each signal because the magnitude of noise and dynamics vary for the different sensors and train passings. Due to this thesis' focus on the matrix method and influence lines, these methods have not been a priority and since correct train velocities are of utmost importance for calculating influence lines.

Since neither of these methods were usable without calibration, an alternative way was developed. This method determined the velocity by recreating the strain signal, like shown in figure 4.6, for various train velocities and minimizing the difference between measured and recreated signal. It utilizes equation 2.7 and requires constant values of axle weights as well as known axle spacings. The only varying factor is the speed used in each iteration to calculate an influence line. A well suited Matlab function "fminsearch", was used to search for the optimal value of train velocity. "fminsearch finds the minimum of a scalar function of several variables, starting at an initial estimate. This is generally referred to as unconstrained nonlinear optimization [7]" This method uses brute force, and its time consumption proved high. The accuracy of this method is believed to be good, but there may be more than one solution satisying the criterias of the algorithm.

The velocities of the trains found through this brute force method is shown in table 4.1, and all plots and results produced have been made using these velocities, except for specificly mentioned cases.

train	3	4	5	6	8
velocity (m/s)	20.99	21.7276	21.4857	16.83	20.591465

Table 4.1: Table of determined train velocities

4.3 Analysis of the influence lines calculated by the Matrix method

For the theoretical strain signal for the simple beam model, shown in 3.3, the Matrix method calulates an almost perfect influence line. Where the only source of error is likely due to noise, or round off errors. The influence line incorporates the properties of a bridge. The analysis of

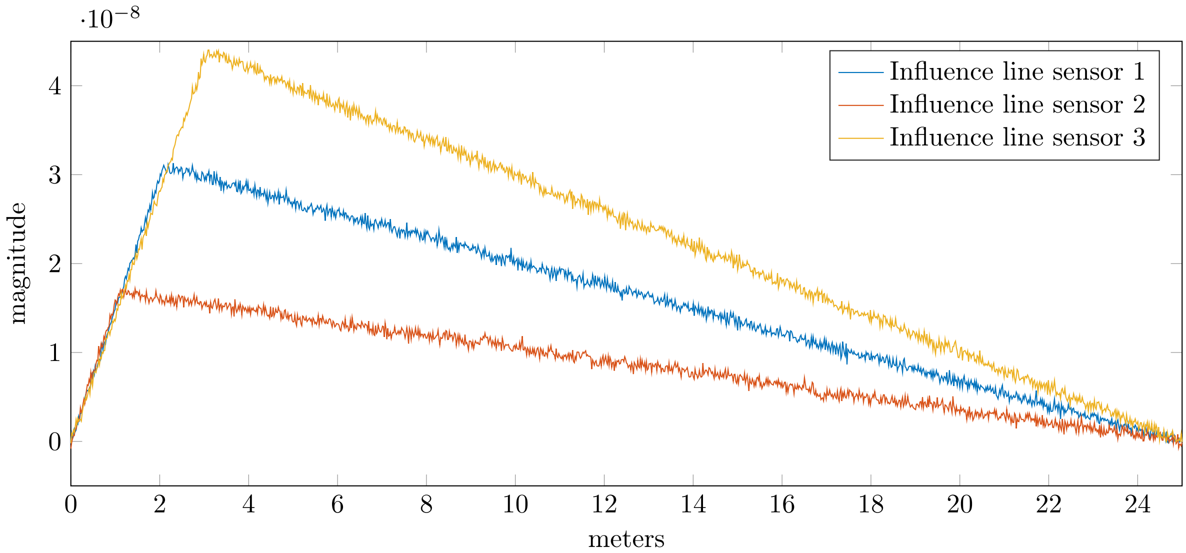


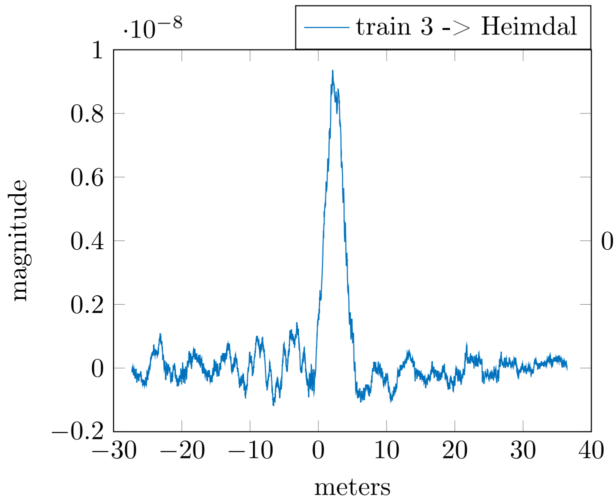
Figure 4.3: Influence line calculated from created strain

the Matrix method is based on 5 different train passings, and 3 sensor readings on each passing. The trains in these in this analysis is all of the type NSB 92 3.7. The weight of each train axle is not known, and therefore the axle weights have been calculated from the gross weight of the wagon and locomotive like shown in table 3.1. Passenger weight, or number of passengers, was not known and has therefore been neglected.

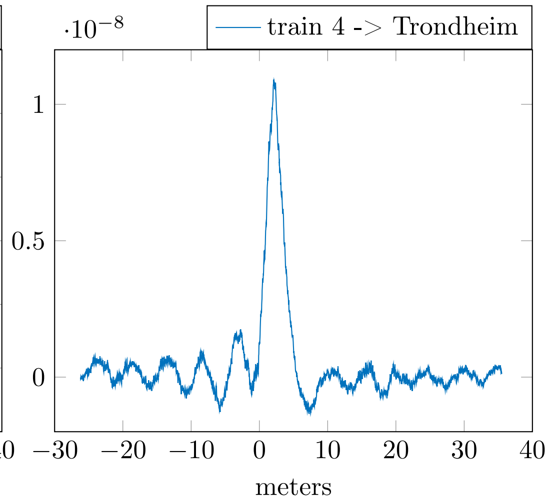
Figure 4.4 show influence lines for 5 different trains passing the same sensor. These influence lines are based on roughly the same number of sampling points, however due to differing train velocities and that the strain signals does not have equal availability of data, since they sampling was started and ended manually, they may differ a little in length. The influence lines have been placed in a reference coordinate system based on the sensor location. The maximum peak location of the influence lines have been placed at the sensors location.

A qualitative assessment of the influence lines in figure 4.4

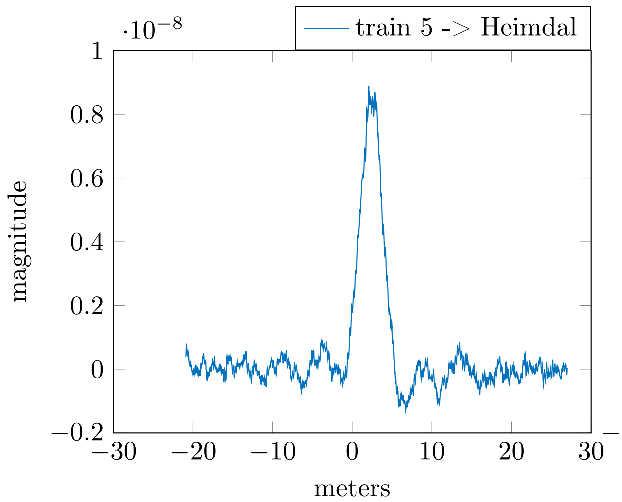
- Train 3 and 5 travels in the same direction, and have a no distinct single peak, while train 4, 6 and 8 have more of a singular peak. This may be due to the different directions of the trains.
  - However other possibilities excist such as train velocity inducing different dynamic effects or that the sensor readings are subjected to noisy creating additional peaks.



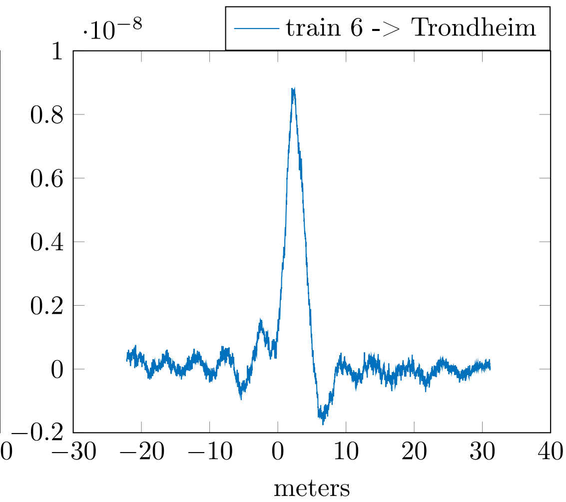
(a) Influence line train 3



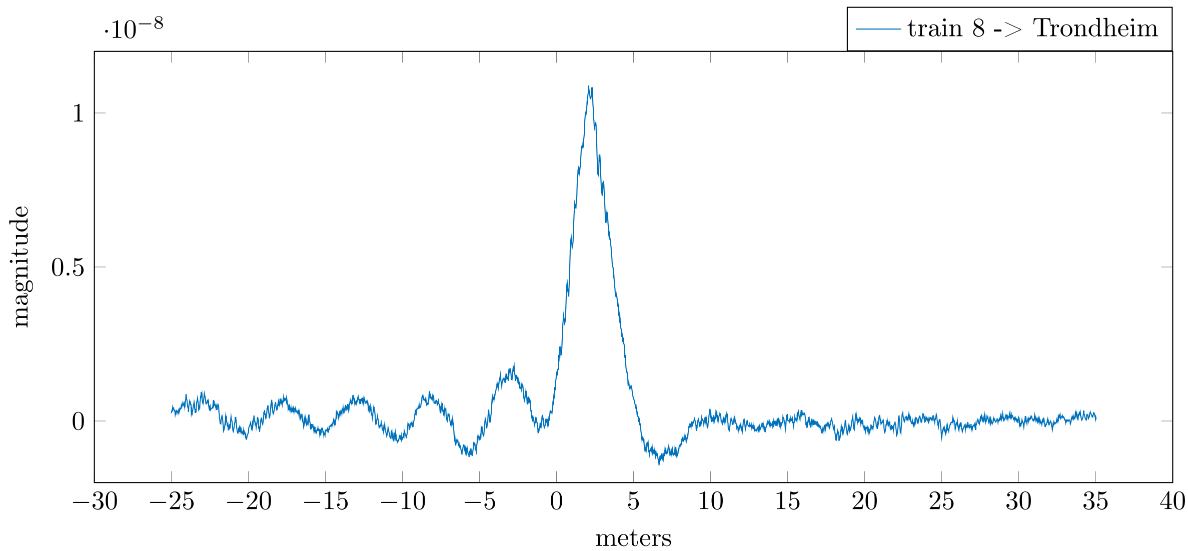
(b) Influence line train 4



(c) Influence line train 5



(d) Influence line train 6



(e) Influence line train 8

Figure 4.4: Influence lines found through the matrix method, for the sensor 1. The legends of the figures tells direction of the trains.

- The different influence lines displays different values of magnitude, the influence line for train 4 and 8 have a magnitude higher than 1×10^{-8}. This is shown more clearly in plot 4.9, showing all the influence lying over each other.

As plainly seen in figure 4.4 there are big differences between the found influence lines. The trains are all of the same type meaning that the magnitudes of the influence lines, which should be the mostly dependent on axle weights, ought to be similar for all train passings. However as discussed in 4.1, the different magnitudes could be explained with the unknown values of axle weights. When the plots are laid on top of each other, as in figure 4.9, it is clearly visible that there is some variation in peak magnitude. Especially train 4 and 8 have a higher maximum peak magnitude than the others.

4.3.1 Accuracy of the Matrix method through recreating the strain signal

One way of examining the accuracy of the matrix method is to recreate the strain signals by assembling the calculated influence lines in the influence ordinate matrix depending on axle spacings, and multiply this matrix with the axle weights vector. Figure 4.5, shows how the signal shown in the method chapter 3.3 created for the beam model, have been recreated using the the influence line calculated through the matrix method. This figure show that the influence

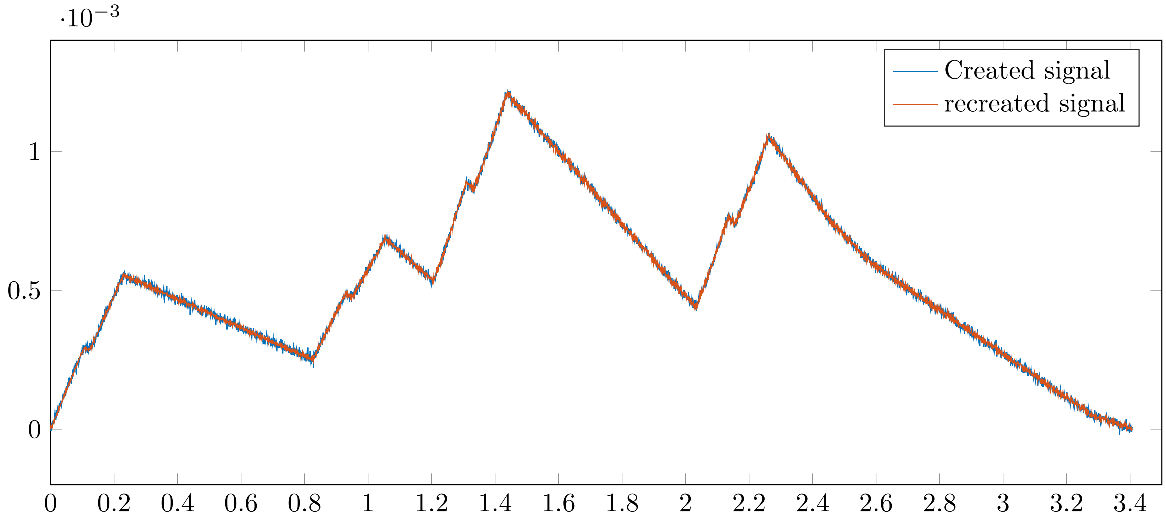
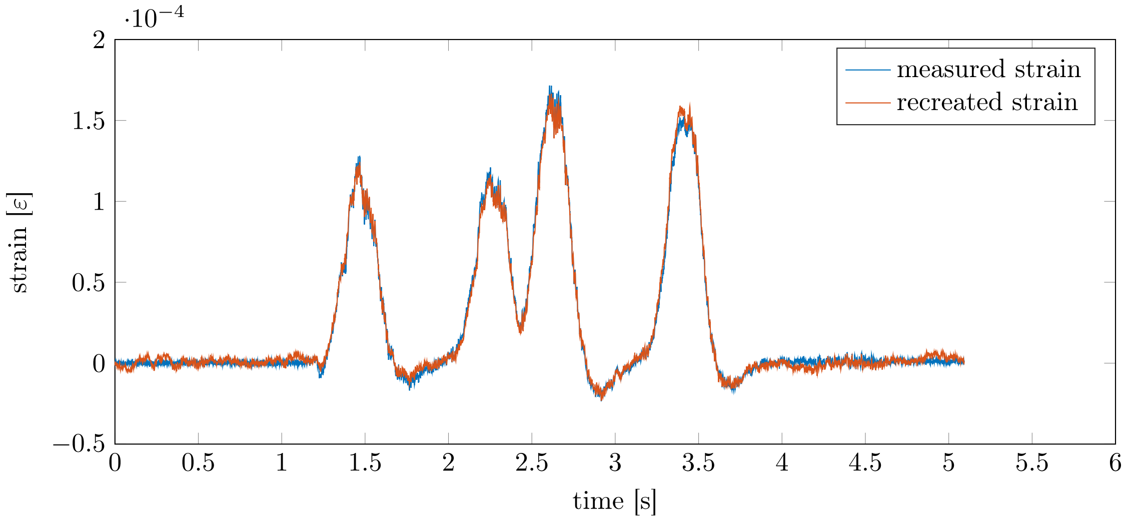


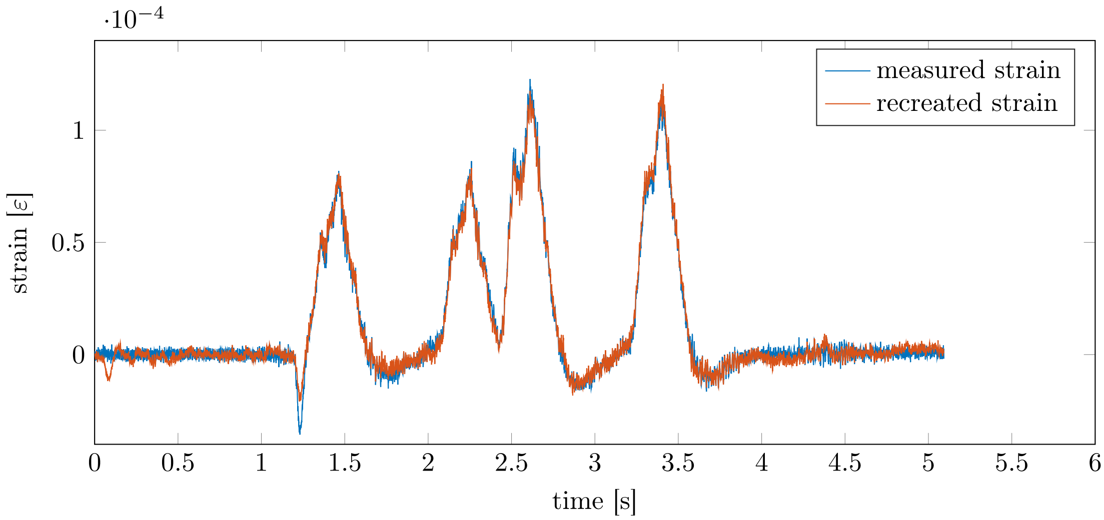
Figure 4.5: Recreated signal shown on top of the created strain signal from 3.3

line created from a theoretical model bridge, were every property of the train is known, is not able to exactly recreate the strain signal. This is believed to be because of white noise added to the signal.

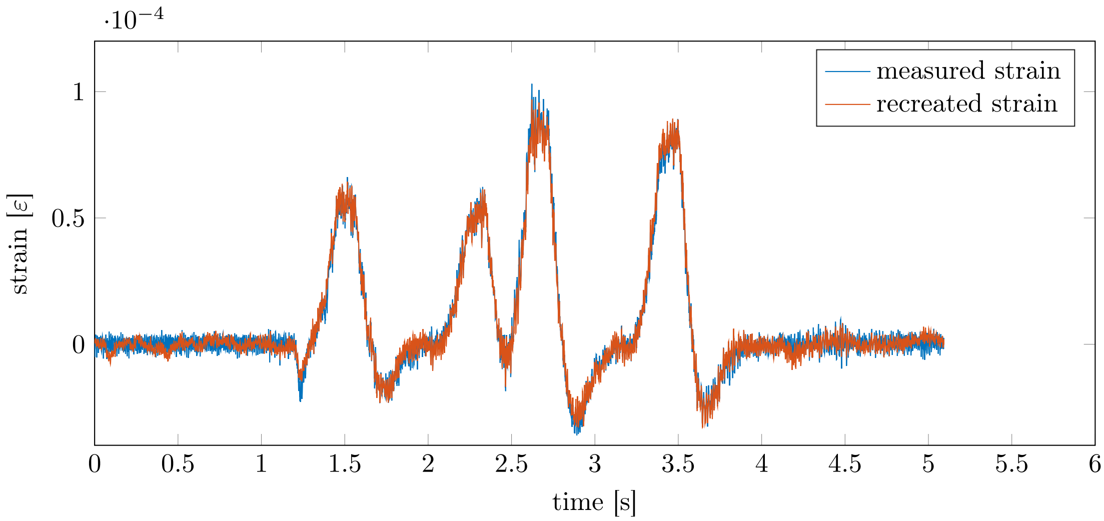
Figure 4.6 shows the strain signals from the three different sensors along with a recreated signal using the found influence lines of the sensors, signals for other trains can be found in appendix A.1. The signals being recreated are long and include sections where little or nothing



(a) Recreated strain atop measured strain, train 3 for sensor 1



(b) Recreated strain atop measured strain, train 3 for sensor 2



(c) Recreated strain atop measured strain, train 3 for sensor 3

Figure 4.6: Recreated strain signals for train 3, overlayed measured signal to demonstrate accuracy of the matrix method

happen during the first and last second of the signal. It is qualitatively difficult to compare the different figures due to the different magnitudes of the strain signals. To identify and compare errors the following equation 4.1, performing least square error will be used.

$$Error = \sum (\varepsilon_{meas} - \varepsilon_{calc})^2 \tag{4.1}$$

The recreated strain signals, see figure 4.6, illustrates the accuracy of the matrix method. As

Error table			
	sensor 1	sensor 2	sensor 3
sum squared signal	$1.3207 \cdot 10^{-5}$	$5.2029 \cdot 10^{-6}$	$3.5630 \cdot 10^{-6}$
train 3	$Error = 6.6307 \cdot 10^{-8}$	$6.3778 \cdot 10^{-8}$	$4.6781 \cdot 10^{-8}$
error %	0.50205	1.22582	1.31297
sum squared signal	$1.6646 \cdot 10^{-5}$	$6.8390 \cdot 10^{-6}$	$3.6794 \cdot 10^{-6}$
train 4	$Error = 7.6854 \cdot 10^{-8}$	$3.9514 \cdot 10^{-8}$	$3.4617 \cdot 10^{-8}$
error %	0.46169	0.57779	0.94084
sum squared signal	$1.2888 \cdot 10^{-5}$	$5.0447 \cdot 10^{-6}$	$3.4902 \cdot 10^{-6}$
train 5	$Error = 5.5810 \cdot 10^{-8}$	$3.4720 \cdot 10^{-8}$	$4.0623 \cdot 10^{-8}$
error %	0.43303	0.68825	1.16391
sum squared signal	$1.5975 \cdot 10^{-5}$	$6.1166 \cdot 10^{-6}$	$3.5417 \cdot 10^{-6}$
train 6	$Error = 8.4405 \cdot 10^{-8}$	$4.2931 \cdot 10^{-8}$	$3.6182 \cdot 10^{-8}$
error %	0.52837	0.70188	1.02158
sum squared signal	$1.6782 \cdot 10^{-5}$	$6.7436 \cdot 10^{-6}$	$3.7381 \cdot 10^{-6}$
train 8	$Error = 6.7858 \cdot 10^{-8}$	$3.0772 \cdot 10^{-8}$	$3.4069 \cdot 10^{-8}$
error %	0.40435	0.45632	0.91138
averaged %	**0.46590**	**0.73001**	**1.0701**

Table 4.2: Errors of the recreated strain signals found in 4.6, rounded to four decimals, strain signal cut to include an extra 600 points of the bridge length

table 4.2 and 4.6, shows the matrix method produces an influence line which recreates the strain signal with very little error. The squared sum of the signals compared to error is very small The error of this recreated strain mostly depends on the accuracy of speed, which decides the sample distance between axles. The averaged errors in the table shows that sensor 3, closest to the middle of the bridge, have the smallest average error. This could indicate that a sensor placement closer to the middle of the bridge resulting less error of calculated influence lines. However many other possibilities may also contribute to this

The differences between the unfiltered and filtered errors, tables 4.3 and 4.4 respectively, are clear but not unexpected. They show that the filtering does not distort the error to an amount which destroys the accuracy of the influence line. The averaged error percentages for

Error table, filtered signals			
	sensor 1	sensor 2	sensor 3
sum squared signal	$1.3207 \cdot 10^{-5}$	$5.2029 \cdot 10^{-6}$	$3.5630 \cdot 10^{-6}$
train 3	$Error = 8.3869{\cdot}10^{-8}$	$Error = 8.1484{\cdot}10^{-8}$	$Error = 7.8551{\cdot}10^{-8}$
error %	0.63503	1.56614	2.20463
sum squared signal	$1.6646 \cdot 10^{-5}$	$6.8390 \cdot 10^{-6}$	$3.6794 \cdot 10^{-6}$
train 4	$Error = 9.3855{\cdot}10^{-8}$	$Error = 5.6308{\cdot}10^{-8}$	$Error = 5.8075{\cdot}10^{-8}$
error %	0.56382	0.82334	1.57837
sum squared signal	$1.2888 \cdot 10^{-5}$	$5.0447 \cdot 10^{-6}$	$3.4902 \cdot 10^{-6}$
train 5	$6.8249 \cdot 10^{-8}$	$5.2464 \cdot 10^{-8}$	$6.9209 \cdot 10^{-8}$
error %	0.52955	1.04000	1.98296
sum squared signal	$1.5975 \cdot 10^{-5}$	$6.1166 \cdot 10^{-6}$	$3.5417 \cdot 10^{-6}$
train 6	$Error = 9.8692{\cdot}10^{-8}$	$Error = 5.2011{\cdot}10^{-8}$	$Error = 4.7314{\cdot}10^{-8}$
error %	0.61781	0.85033	1.33589
sum squared signal	$1.6782 \cdot 10^{-5}$	$6.7436 \cdot 10^{-6}$	$3.7381 \cdot 10^{-6}$
train 8	$Error = 8.7170{\cdot}10^{-8}$	$Error = 5.0457{\cdot}10^{-8}$	$Error = 6.2777{\cdot}10^{-8}$
error %	0.51943	0.74823	1.67938
average %	**0.57313**	**1.0056**	**1.7562**

Table 4.3: Errors of the recreated strain signals with original signal filtered for noise above 20 Hz, rounded to four decimals and using the same setup as for the previous model 4.2

the different sensors in the error tables 4.4, 4.3 and 4.2 all show sensor 1 as being better able to recreate the strain signal values. This may be because only the signals from sensor 1 has been used to estimate the train velocities, and that one signal alone may produce a value better suited to that particular signal. Due to the main focus of this thesis being on other areas of BWIM systems, this has not been investigated further than this. Other possible reasons for this observed difference between error percentages are that some sensor locations are better suited for BWIM, or that the signals with lower values of strain are more susceptible to noise.

To really compare the methods of filtering however the found influence lines should be used to calculate axle weights. Averaging of the influence lines gives the following plots. An interesting discovery by studying these table, is that the longer the produced influence line becomes the more accurately it reproduces the strain. As figure 4.1 shows, the trains affects the sensor over a 2-3 second period. And the influence of a bogie stops shortly after it has passed the sensor, as the flatness after the last peak indicates. This shows that a bridge of this type will have a very local deformation due to loading. This means that a influence line for a sensor location on a bridge type like this will be short compared with bridge length. Influence lines made with the minimal cutting points can be seen in figure 4.7.

Error table, minimal influence lines			
	Trondheim sensor	middle sensor	Heimdal sensor
sum squared signal	$1.3205 \cdot 10^{-5}$	$5.1993 \cdot 10^{-6}$	$3.5575 \cdot 10^{-6}$
train 3	$Error = 8.3046{\cdot}10^{-8}$	$Error = 6.9250{\cdot}10^{-8}$	$Error = 5.6861{\cdot}10^{-8}$
error %	0.62891	1.33192	1.59832
sum squared signal	$1.6634 \cdot 10^{-5}$	$6.7644 \cdot 10^{-6}$	$3.6746 \cdot 10^{-6}$
train 4	$Error = 1.0317{\cdot}10^{-7}$	$Error = 5.0548{\cdot}10^{-8}$	$Error = 4.0564{\cdot}10^{-8}$
error %	0.62024	0.74726	1.10391
sum squared signal	$1.2886 \cdot 10^{-5}$	$5.0407 \cdot 10^{-6}$	$3.4850 \cdot 10^{-6}$
train 5	$7.5816 \cdot 10^{-8}$	$4.4896 \cdot 10^{-8}$	$5.1032 \cdot 10^{-8}$
error %	0.58835	0.89067	1.46433
sum squared signal	$1.6308 \cdot 10^{-5}$	$6.3414 \cdot 10^{-6}$	$3.7159 \cdot 10^{-6}$
train 6	$Error = 1.1471{\cdot}10^{-7}$	$Error = 5.0396{\cdot}10^{-8}$	$Error = 4.1867{\cdot}10^{-8}$
error %	0.70340	0.79471	1.12670
sum squared signal	$1.6795 \cdot 10^{-5}$	$6.6767 \cdot 10^{-6}$	$3.7751 \cdot 10^{-6}$
train 8	$Error = 9.2468{\cdot}10^{-8}$	$Error = 3.8699{\cdot}10^{-8}$	$Error = 4.0678{\cdot}10^{-8}$
error %	0.55057	0.57961	1.07752
average %	**0.61829**	**0.86883**	**1.2742**

Table 4.4: Error table for minimal influence lines as in figure 4.7

4.4 Dynamic effects

The dynamic effects can clearly be seen in the plots of the influence lines for the various train passings. They appear as oscillations in the plots, and are more visible in the low magnitude areas of the influence line. These oscillations vary from train to train making it clear that the dynamic effects depends on the train. The varying influencing factors may be train speed and weight. In the source code producing these influence lines an assumption of train weight has been made, which makes all train axles equal in weight. What is interesting is the effects of an approaching train, which clearly induces oscillations in the bridge even though the train is as far as 40 meters away from the beginning of the bridge. The differences between the dynamic effects for the train passings may relate to velocity, axle weights and train acceleration (there may be more causes).

These dynamic effects are unwanted in the static influence line. In theory, averaging enough influence lines should reduce these effects enough to get usable data. This thesis does not contain enough train passings to achieve this. Wrongly determined train velocity is a cause of oscillating influence lines, and can easily be mistaken for dynamic effects. Figure 4.8 is an example of a influence line determined from a wrongly set speed. A general formula for identifying influence

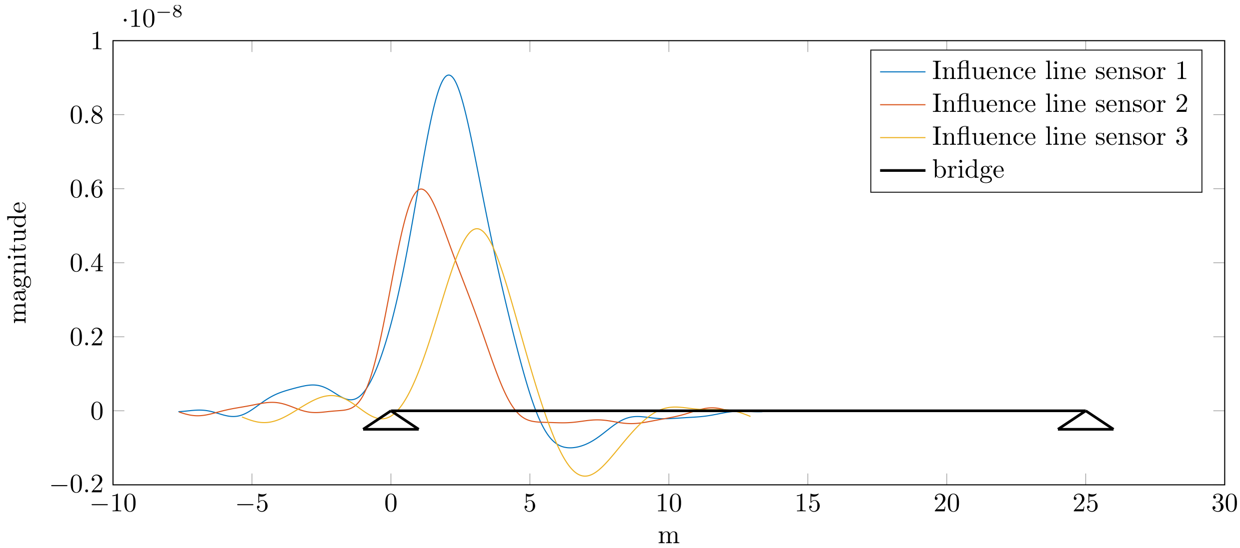


Figure 4.7: Influence lines for the sensors, calculated by the matrix method using a minimal strain signal

lines with too much oscillation should be developed. One way could be to use table 4.2 and exlude the trains which dominates error, or that differs most from the other trains.

The support towards Trondheim is of a special nature, it is connected to a very little bridge spanning perhaps 2 meters which cars may pass under, this can be seen in construction drawing in appendix B. This may affect the train's entry and cause dynamic effects. It also provides a problem when determining what should be part of a final influence line, or which parts of the influence line that is actually staticly influenced by the train on the bridge. One way to do it would be to simply cut the influence line at the samples corresponding to the bridge, however that does not seem likely to be a very good solution. Another way would be to smooth the influence line to the point where the entry part becomes itegrated with the the major influence line peak, which would result in a greatly distorted peak and is therefore not a good solution. Calibration could determine what parts of the influence lines are actually needed.

4.5 Averaging calculated influence lines

To obtain as good an influence line as possible, averaging of the calculated influence lines should provide representative values for the various signals.

Figure 4.9 shows all the influence lines for one sensor, in one figure, which highlights the differences and similarities between the figure. Clearly two of the influence lines, train 4 and train 8 has a maximum peak magnitude which differs from the others. These two trains both travels the bridge in the same direction, which could be a cause for the differing magnitudes, however train 6, which also travels the same direction, does not follow this trend and in fact aligns with the other peaks of train 3 and 5. Based on this it can be assumed that direction of

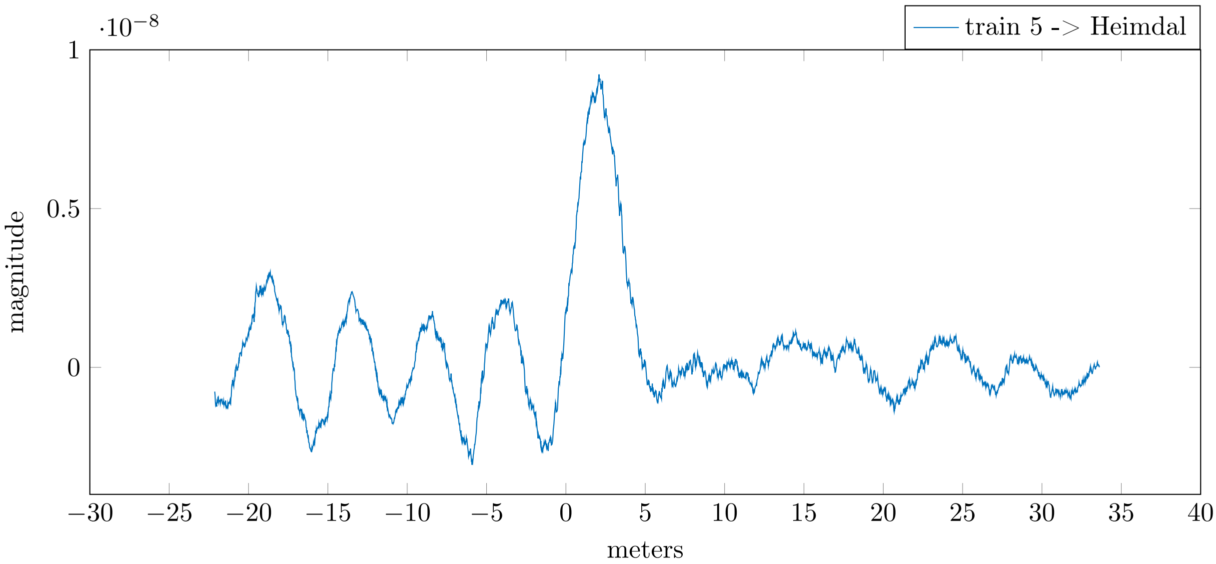


Figure 4.8: Influence line train 5, showing how how a wrongly set speed induces high amplitude oscillations

the train should not affect the magnitude of the maximum peak.

Another hypothesis for the differing peak heights, could be that the trains differ greatly in actual axle weights. A heavy train would cause higher values of measured strain and the measured strain is what the matrix method uses to find the influence lines. The values of axle weights used to produce the influence lines of the bridge are fixed at the values of a empty train. A quick study of equation 2.9, shows that increasing the values measured strain also would increase the values of the influence line. This is therefore a likely cause of differing magnitudes.

The average of these influence lines will have a maximal peak magnitude somewhere between the peaks of train 3,5 and 6 and train 4 and 8. This would cause problems when calculating the axle weights, the axle weights of train 3, 5 and 6 would be underestimated, and the axle weights of train 4 and 8 would be overestimated. This effect can be seen in the tables 4.5 and 4.6, showing calculated axle weights using this averaged influence line. The equivalent of figure 4.9 for sensors 2 and 3 can be found in appendix A.10 and A.11. These collection of influence lines also display a differing in magnitudes of the influence lines, with some differences. For sensor 2 train 4 and 8 still has higher maximum values, but train 8 produces a lower value of maximum compared with train 4. For sensor 3 the efect of differing magnitudes are almost invisible, for this sensor all trains seems to produce similar values except for train 6. This is also visible in table 4.5, where the axle weights for sensor 3 shows train 6 having the highest total value.

Another factor which could be the source of these effects are the velocity of the trains. A wrongly determined velocity causes oscillations in the influence lines as discussed previously, and maybe this also could cause differing maximum peak values. It may also be that different velocities could cause differing entry effects, which would provide the influence line a wrong value at the beginning of the bridge.

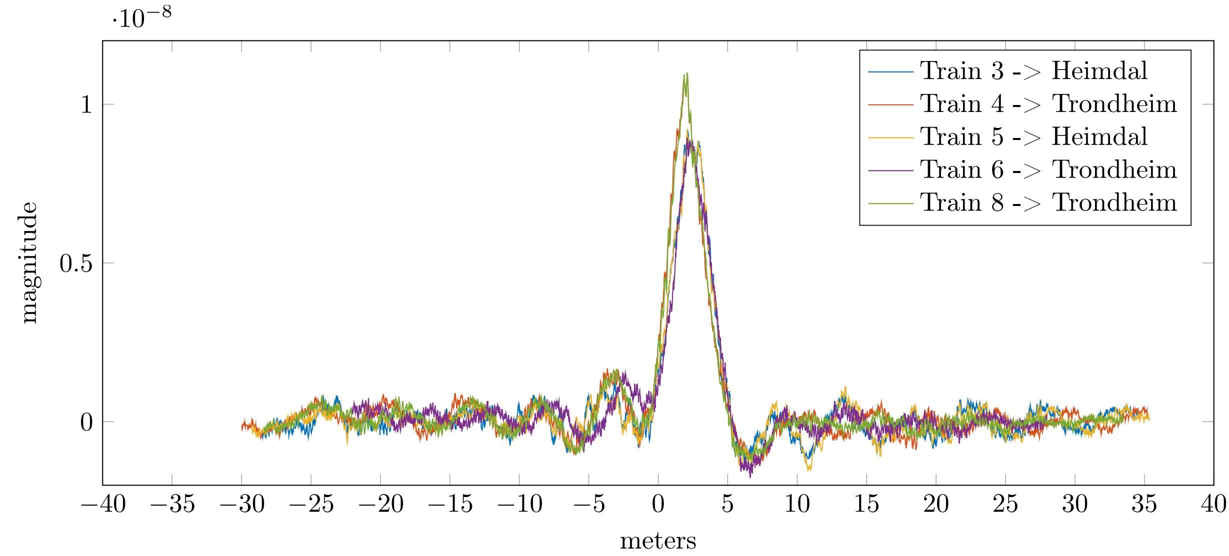


Figure 4.9: Influence lines from figure 4.4 on top of each other for sensor 1

The identified average influence lines used for calculations in the remaining thesis are shown in figure 4.11, 4.12 and 4.7. These figures clearly show reduction of dynamic effects compared to the influence lines of figure 4.4. The averaged influence lines are shorter than the original influence lines of this chapter.

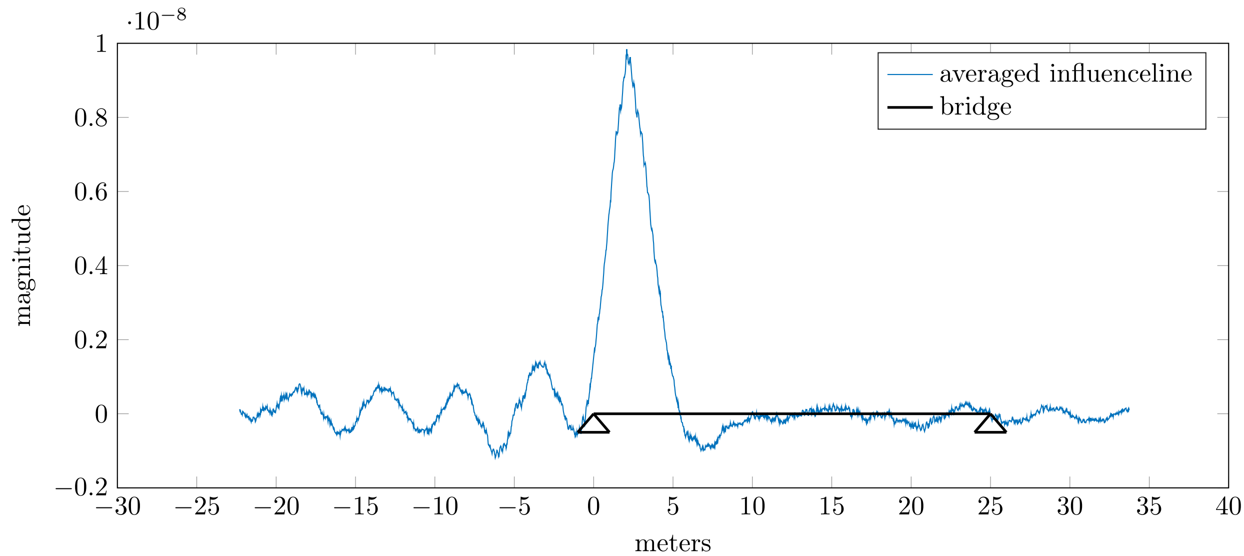
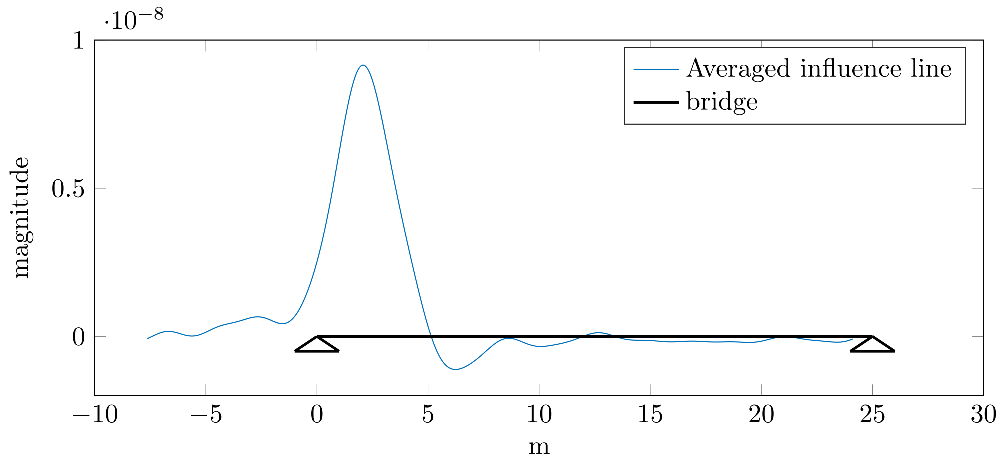
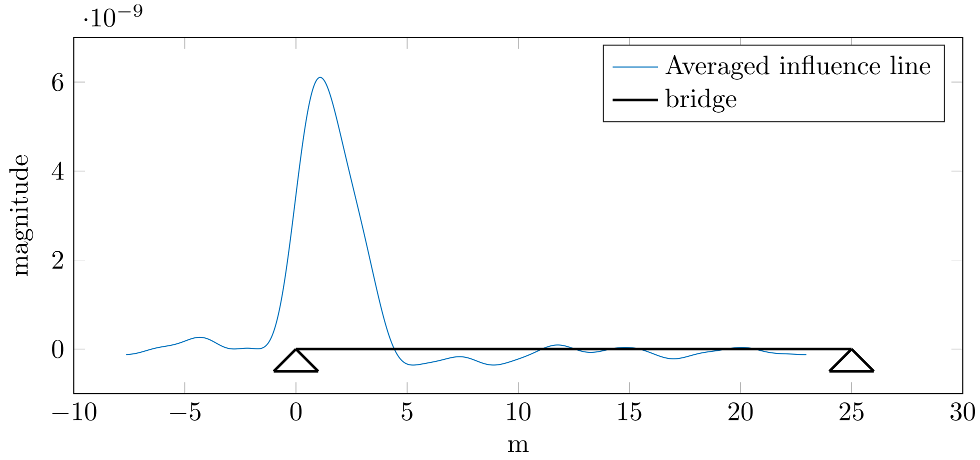


Figure 4.10: Averaged of the 5 trains

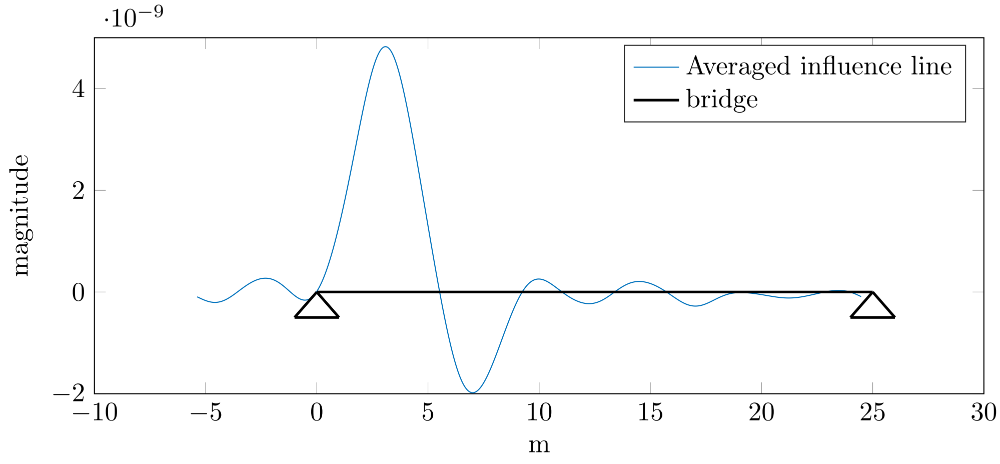
A possible way to place the found influence line is shown in figure 4.10, which places the influence line in the assumed position on the bridge. The maximum magnitude of the influence line should be found at the sensor location, thusly the average influence line has been placed in the corrdinate system of the bridge accordingly. There is however the problem of noise, which makes identifying the actual max peak difficult. Filtering the signals so that a singular smooth maximum peak can be identified. This could distort the actual signal, but is the way this has



(a) Averaged influence line for sensor 1



(b) Averaged influence line for sensor 2



(c) Averaged influence line for sensor 3

Figure 4.11: averaged influence lines used to calculate axle weights

been done in this thesis.

4.6 Using calculated influence lines

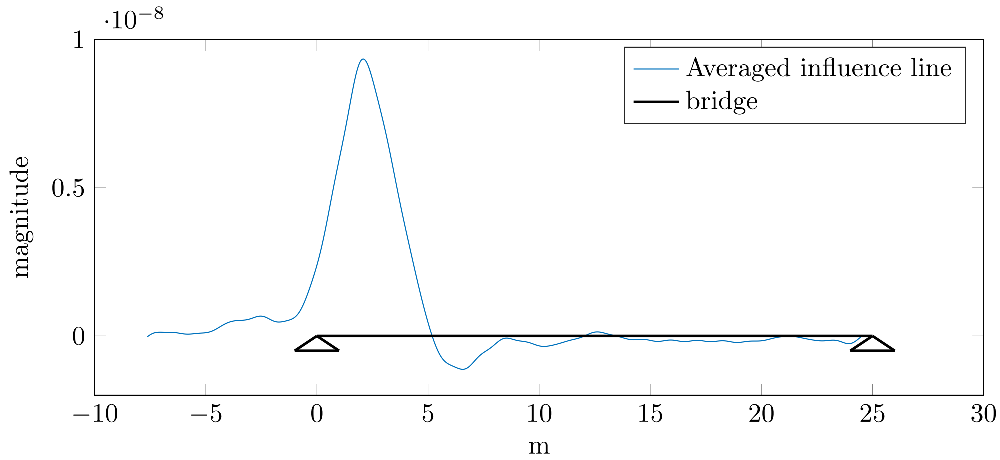
The Matrix method calculates an influence line vector, which is perfectly suited to that specific strain signal. The signals will however vary from train to train, both in length and magnitude. This means that the influence line for the sensor needs to be adapted to the strain signal. To perform a standard axle weight calculation, the influence line is required to be correctly aligned with the strain signal. The first peak of the strain signal, corresponding to the first axle of the train, should occur at the same location as the peak of the influence line which should be precisely at the sensor location.

Identifying the first peak of the strain signal is subject to noise which corrupts any reading of peaks in the raw strain signa. Therefore filtering of noise is needed to correctly identify the signals peaks. A trains axle spacings, as seen in 3.7 which is the train type of the measurements, consists of short axle distances of about 2.5 meters. If the axle spacing between two axles are short compared to the bridge, or more specifically short compared to the width of the influence line, they both influence the signal simoultaneously and the peaks corresponding to the two axles thus lies very close to each other. The filtering can therefore not be to hard or soft, which results in problems when trying to automate the procedure of identifying axles.

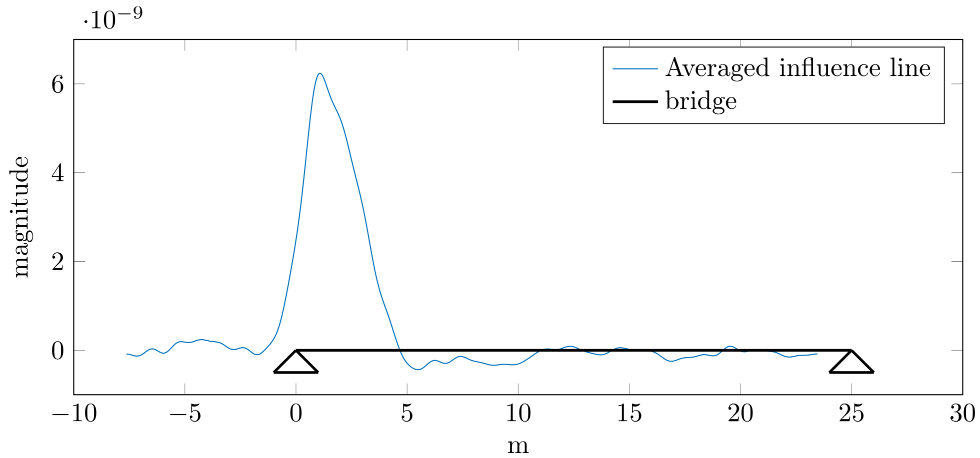
To correctly align the strain signal and influence line, the matlab code used in this thesis first smooths the strain signal to a degree where the desired number of peaks are identifyable before using matlabs findpeaks [6] procedure to find the peak locations, like seen in figure 4.13. This functions finds the local maxima of input vector and have the option of specifying conditions for the maxima. When trying to place the influence line, it was found that axle detection needs to be very accurate for the calculation of axle loads. When using the method described above, with filtering to a degree where 8 peaks are found and to check how those peaks correspond with the known train's axle distances, proved to be accurate in some cases and very wrong in other cases. A wrongly found axle peak could for instance result in negative axle weights, and generally wrong axle weights. A more general method which seems to place the influence better is to filter the signal to a degree where only the major peaks are found. The location of the first such peak should roughly correspond to the centre between closely spaced axles, or a bogie centrum, on a train. Since the trains axles spacings are known, a successfully identified bogie location should place the influence line with a decent accuracy.

4.7 Calculating the axle weights

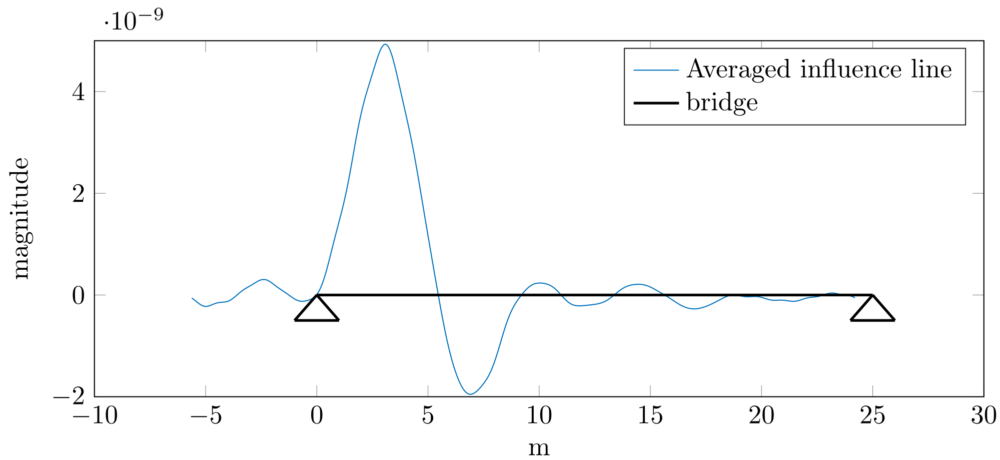
The system setup described in section 3.2, gives three different locations for measuring strain and so thus three diffferent influence lines generated by the BWIM program. When calculating



(a) sensor 1



(b) sensor 2



(c) sensor 3

Figure 4.12: averaged influence lines, based on filtered strains, used to calculate axle weights

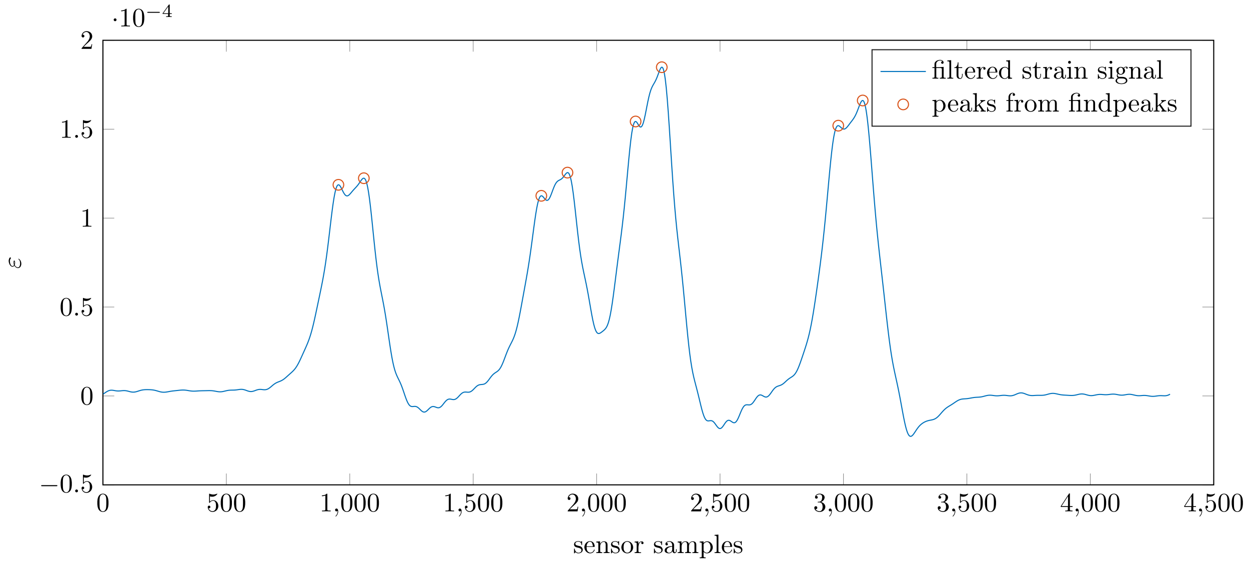


Figure 4.13: Axle peaks in strain signal

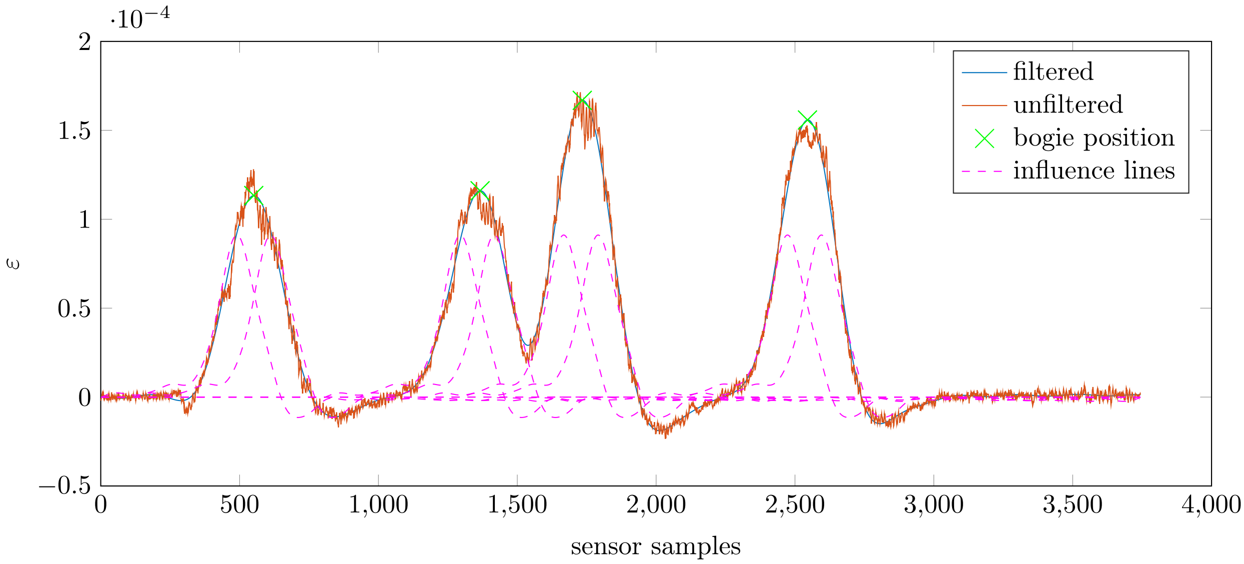


Figure 4.14: Placement of influence lines, based on bogie peaks in signal. The influence lines shown are scaled to fit strain signal magnitude.

the axle weights corresponding to each train, this will give three different estimates of the axle weights. However, since data of actual axle weights of the trains are unknown, estimating correctness of the BWIM can not be done through comparing known and calculated axle weights.

Figures 4.12 and 4.11 are the influence lines used to calculate the axle weights in the tables 4.6 and 4.5. By studying the different influence lines, it is clear that the visible differences between the two variants are minimal. This can also be seen in their respected tables. The influence lines produced by filtered strain seems to produce a influence line of slightly lower magnitude, which when used to calculate axle weights results in slightly different values. Sensor location clearly distinguishes the influence lines:

- The influence line from sensor 1, the middle section sensor, appear to be a mixture of the influence lines from the other sensors.
  - Sensor 3 is closer to the end of the bridge's first section, and this can clearly be seen through the negative influence after the first 5 meters of the bridge.
  - Sensor 2 has lesser negative magnitude after the first 5 meters. The entry effects of the averaged influence lines also appears to be least significant for this sensor location.
- Sensor 3 is influenced by a larger section of the bridge.

The axle weights in table 4.6 is calculated using the influence lines from figure 4.12 . These The axle weights calculated for the minimal influence lines is similar to what is shown in the tables 4.6 and 4.5. A shorter influence line may still contain dynamic effects, but likely less than longer influence lines.

4.7.1 Accuracy of axle weights

As seen in tables 4.6 and 4.5, there are differences between the calculated axle weights for each sensor. The values for the different axles should be relatively similar for each calculation, but for some of the signals it is clear that values vary with up to 2000 kg which unlikely is explainable by passenger distribution in the train. The axle weights of a bogie should be fairly equal, which the tables are not showing. A more reasonable explanation for these differences from axle to axle could be the placement of the influence line representing the axle, as has been discussed in 4.6. These are errors which may have one or more reasons.

The ratio tables, 4.10, 4.9 and 4.8, highlight the differences and similarities between the influence lines. The ratio between axle weights for the different versions of the influence line differ little from each other, all ratios are within 10 % showing that the calculated gross train weights are reasonably constant from sensor to sensor. The tables show that the difference between minimal and standard length influence line are small, while the influence lines calculated from filtered signals have the highest values of difference. The tables also indicate that sensor location is of significance. Sensor 1 and sensor to produce the most consistent ratio values, where calculated gross vehicle weight is higher for every train compared with the same values

	trains and their axle weights for sensors														
	sensor 1					sensor 2					sensor 3				
axle	train 3	train 4	train 5	train 6	train 8	train 3	train 4	train 5	train 6	train 8	train 3	train 4	train 5	train 6	train 8
1	8563	10689	8578	11156	10617	9006	11278	9570	11195	11233	8341	8763	8402	9111	8532
2	9343	10379	9170	10237	10284	7814	8628	7491	8176	8295	9581	9820	9440	10945	10043
3	8709	10294	8817	11353	10353	9521	11446	9983	11940	11668	8837	8563	9203	8752	8320
4	9057	9868	8451	10400	10285	8214	8586	7351	8336	8697	9073	9626	8547	10479	10262
sum car	35672	41230	35016	43146	41539	34555	39938	34395	39647	39893	35832	36772	35592	39287	37157
5	13392	15615	13546	15879	14865	14904	18402	15379	17434	17489	14064	14462	14660	13515	13475
6	14581	14893	13859	15985	16313	13059	13336	11674	13391	14079	16116	15509	15121	18038	17548
7	11303	15097	11479	15656	14380	13238	17679	13678	17332	17278	12374	13561	12595	13615	12636
8	14184	12962	13616	13549	14350	12496	10913	11196	10910	12026	14788	13792	13933	16003	15501
sum loc	53460	58567	52500	61069	59908	53697	60330	51927	59067	60872	57342	57324	56309	61171	59160
sum tot	89132	99797	87516	104215	101447	88252	100268	86322	98714	100765	93174	94096	91901	100458	96317

Table 4.5: Table of axle weights for averaged influence lines, all trains

	trains and their axle weights for sensors														
	sensor 1					sensor 2					sensor 3				
axle	train 3	train 4	train 5	train 6	train 8	train 3	train 4	train 5	train 6	train 8	train 3	train 4	train 5	train 6	train 8
1	8819	10971	8837	11301	10858	9788	12060	10353	11531	11859	8042	8436	8093	8916	8241
2	9106	10086	8932	10052	10046	6847	7536	6423	7435	7367	9835	10100	9715	11083	10263
3	8940	10522	9055	11488	10561	10343	12185	10765	12282	12338	8625	8317	8994	8561	8081
4	8822	9620	8207	10252	10066	7231	7577	6313	7563	7740	9376	9928	8867	10687	10522
sum car	35687	41199	35031	43093	41531	34209	39358	33854	38811	39304	35878	36781	35669	39247	37107
5	13772	16046	13938	16095	15283	16131	19592	16561	17926	18582	13572	13946	14169	13138	12950
6	14255	14494	13517	15729	15949	11548	11597	10066	12196	12487	16510	15931	15561	18235	17885
7	11696	15513	11883	15874	14771	14504	18803	14944	17770	18271	11909	13092	12127	13310	12179
8	13866	12567	13280	13332	13990	11051	9210	9625	9748	10496	15178	14230	14359	16217	15850
Sum loc	53589	58620	52618	61030	59993	53234	59202	51196	57640	59836	57169	57199	56216	60900	58864
Sum tot	89276	99819	87649	104123	101524	87443	98560	85050	96451	99140	93047	93980	91885	100147	95971

Table 4.6: Table of axle weights for averaged influence lines, where strains have been filtered, all trains

	trains and their axle weights for sensors														
	sensor 1					sensor 2					sensor 3				
axle	train 3	train 4	train 5	train 6	train 8	train 3	train 4	train 5	train 6	train 8	train 3	train 4	train 5	train 6	train 8
1	8797	10984	8905	11393	10746	9139	11473	9802	11373	11272	8458	9126	8626	9632	8771
2	9431	10467	9162	10726	10627	7961	8553	7503	8949	8582	9677	9765	9427	11362	10232
3	8860	10476	9080	11255	10311	9479	11454	10045	11886	11452	8855	8918	9344	9046	8444
4	8956	9718	8217	10956	10475	8324	8475	7317	9240	9024	8845	9098	8134	10820	10192
sum car	36044	41645	35364	44330	42159	34903	39955	34667	41448	40330	35835	36907	35531	40860	37639
5	13598	15795	13884	16239	14856	15072	18646	15682	17677	17494	14189	14869	14916	14155	13712
6	14769	15069	13863	16527	16865	13304	13285	11703	14454	14578	16245	15406	15067	18496	17837
7	10980	14773	11322	15297	13793	12888	17424	13476	17120	16756	11988	13622	12372	13889	12354
8	13984	12654	13245	13941	14430	12477	10492	10988	11852	12197	14577	13214	13550	16187	15341
sum loc	53331	58291	52314	62004	59944	53741	59847	51849	61103	61025	56999	57111	55905	62727	59244
sum tot	89375	99936	87678	106334	102103	88644	99802	86516	102551	101355	92834	94018	91436	103587	96883

Table 4.7: Table of axle weights for minimal averaged influence lines

Gross weight train					
	train 3	train 4	train 5	train 6	train 8
sensor 1	89132	99797	87516	104215	101447
sensor 2	88252	100268	86322	98714	100765
ratio:	0.99013	1.00472	0.98636	0.94722	0.99328
sensor 1	89132	99797	87516	104215	101447
sensor 3	93174	94096	91901	100458	96317
ratio:	1.04535	0.94287	1.05011	0.96395	0.94943
sensor 2	88252	100268	86322	98714	100765
sensor 3	93174	94096	91901	100458	96317
ratio:	1.05577	0.93845	1.06463	1.01767	0.95586

Table 4.8: Ratio table showing the ratio between gross train weight for the different sensors, using values from table 4.5

Gross weight train					
	train 3	train 4	train 5	train 6	train 8
sensor 1	89375	99936	87678	106334	102103
sensor 2	88644	99802	86516	102551	101355
ratio:	0.99182	0.99866	0.98675	0.96442	0.99267
sensor 1	89375	99936	87678	106334	102103
sensor 3	92834	94018	91436	103587	96883
ratio:	1.03870	0.94078	1.04286	0.97417	0.94888
sensor 2	88644	99802	86516	102551	101355
sensor 3	92834	94018	91436	103587	96883
ratio:	1.04727	0.94205	1.05687	1.01010	0.95588

Table 4.9: Ratio table showing the ratio between gross train weight for the different sensors, using values from table 4.7

Gross weight train, from filtered signal					
	train 3	train 4	train 5	train 6	train 8
sensor 1	89276	99819	87649	104123	101524
sensor 2	87443	98560	85050	96451	99140
ratio:	0.97947	0.98739	0.97035	0.92632	0.97652
sensor 1	89276	99819	87649	104123	101524
sensor 3	93047	93980	91885	100147	95971
ratio:	1.0422	0.94150	1.0483	0.96181	0.94530
sensor 2	87443	98560	85050	96451	99140
sensor 3	93047	93980	91885	100147	95971
ratio:	1.0641	0.95353	1.0804	1.0383	0.96804

Table 4.10: Ratio table showing the ratio between gross train weight for the different sensors, using values from table 4.6

from sensor 2. The same can not be said for the comparison of sensow 1 and 3 as well as sensor 2 and 3, where the ratio values vary from over 1 to under one for different trains. These differences can be seen by studying the influence lines for the different sensors. The influence lines for sensor 1 and 2 are visually similar while the influence line for sensor 3 have the lowest peak value but appears to have a wider zone of influence meaning that the sensor is affected more from the other sections of the bridge.

Likley sources of error in calculated axle weights:

- Wrongly determined train velocity - resulting in incorrect influence lines, and error in alignment of influence lines with strain signal.
- Peak detected by placement algorithm is wrong.
- Averaged influence line does not represent the strain signal, that is the axle weights used to calculate the influence lines was not correct and resulted in too high or low magnitude of the influence lines peak.
- The sensors may not be correctly calibrated, resulting in differences in axle weights from sensor to sensor. This can be controlled by calculating the ration between the same axles for different sensors.

4.8 Calibration and verification of the system

Attempts were made to aquire a signal able to calibrate and verify the system described by thesis. The freight train has one constant which the other trains do not have, a locomotive which will have axle weights approximately equal the given properties of the locomotive as listed in 3.4.

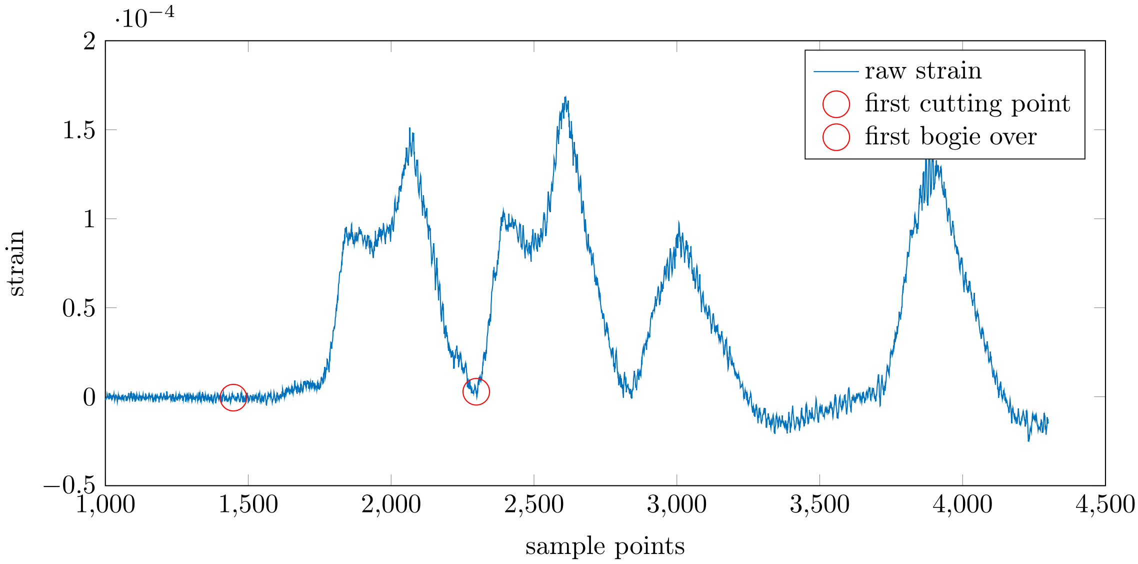


Figure 4.15: Figure showing how extraction of the locomotive data in the signal

To be able to use the locomotive for these purposes, required special attention of the cutting of the strain signal of train 7 4.2e. Through the BWIM program it was tried to identify the first 2 major peaks of the signal corresponding to the 6 axles of the locomotive and cut the signal accordingly. The strain signal however proved difficult or impossible to cut correctly, due to the length of the locomotive and the width of the influence line the next axle after the locomotive also influenced the signal, which would affect the results.

The best suited sensor for this task proved to be the sensor closes to the support on the side towards Trondheim. Figure 4.15 shows the first peaks of the strain signal for this sensor, where the first two major peaks corresponds to the axles of the locomotive. The red circles named first cutting point and first boigie over, shows a possible cut of the signal could be made. The third and fourth major peak indicates axles of the vagons. The two first peaks should ideally have had the same level of magnitude, the fact that they do not shows that the first and second set of axles influence the sensor at the same time. The second point also is raised above the first point, which also is the case for the next peak corresponding to vagon axles. A safe signal could based on this not be found to perform calibration with, as it would provide a error. Therefore this a calibration of the sensors have not been achieved in this project.

If this calibration locomotive had been found usable, better estimates of the axles weights of the other trains could have been identified. It would also point to where the errors of the system are the most crucuial.

During the time spent in this thesis, attempts were mad to validate the BWIM Matlab program as well as the resulting influence lines. Due to later discovered bugs in the program causing a systematic error in the averaged influence lines, it was for some time believed that the sensors were uncalibrated. With the correction of this bug it is no longer possible to identify signs of this. However some time went to investigate how the sensors could be calibrated through the BWIM program. One possible way was to calibrate the sensors based on the resulting axle weights for a known train. This also coincides with how the system best could be validated, by using the identified influence lines to calculate the axle weights of a train with known properties. This would give the actual errors of the calculated influence lines, and perhaps give an insight to what what are dynamic effects in the influence lines. The following scheme was made to scale uncalibrated sensors.

1. Have a train, of which the known properties are velocity, axle distances and axle weights, perform one or more runs in both directions.
2. The obtained strain signals from these passings are used along with the Influence line to calculate the axle weights for at least one sensor.
3. The resulting axle weights should have a constant ratio between the same axles for different sensors.
4. The axle weights are scaled to equal the known values. These scalars is the calibrating constants for the sensors.
5. The scalars obtained could be used directly on the signal data, but the only part of the BWIM which directly requires this scaling for correct results are the calculated axle weights.

5. Conclusion and summary

The goal for this thesis was to create and analyze a BWIM system developed by the author. This concluding chapter will summarize the essential results from the analysis. It will thereafter seek to answer the initial goals from the research objectives 1.2.

5.1 How does the matrix method perform

The plots showing recreated strains, figure 4.6 and appendix figures A.1 to A.4 show the good accuracy of the matrix method. Given accurate values of train velocity and axle distances the individual influence lines are able to almost exactly recreate the signals. This means that the matrix method by itself is a superior tool, but that it requires high levels of accuracy from the rest of a the BWIM system.

The matrix method runtime depends on the signal length and number of train axles. Relying on the symmetry of the matrices it is possible to only form half the matrix and use the transpose operation to form the full a matrix, which saves computational time.

The problem with the matrix method is that it is subjected to dynamic effects from the bridge. This can be solved by having several calibration runs in both directions and average the resulting influence lines. A train moving at very low velocity would likely also help minimize those dynamic effects and together with several calibration runs this would likely eliminate or make the the dynamic effects negligible.

The matrix method is easily implemented using the theory described in section 2.2.2.

5.2 The placement algorithm

When it came to aligning the identified influence lines with the equation system, several two different approaches was made both involving peak identification. Even with noise levels of the signals identifying individual peaks, representing axles, for alignment was found possible to do for each signal but no general method was successfully developed which was able to do this for every signal. This method also increases error. Therefore a better solution proved to be identification of the signal peaks produced by a bogie. This was done through smoothing the signal to the point where individual axles are not visible. Section 4.6 shows how the influence lines have been placed according to strain signal. This method has not been controlled properly, but seems to result in satisying accuracy. It does not require any special input from user, and is likely reliable. That is, it will not increase the error of future calculation with much, as it's accuracy depends much on other parts of the system.

This method can easily be improved, instead of using only the first peak of the strain signal to align the influence lines, all the peaks could be used to identify a even safer placement. Possibly an optimization routine, much like the one used in this thesis to find the trains velocities, could be used to find the best possible placement of the influence lines. One way of performing this optimization of alignment could be:

1. Use the placement found by the existing method as an initial guess of placement.
2. For each iteration of optimization, the axle weight is calculated and used to recreate the strain signal.
3. A mean square error or similar function, is calculated
4. The alignment of influence lines which minimizes this error will likely be a good or perfect placement.

This way of optimizing placement of influence lines could be used in a similar manner to find the axle distances of the train. That way detection of peaks corresponding to axles would not be necessary, also this method likely would be less subjected to, or even independent of, noise. However such an algorithm could identify solutions with minimal errors but which do not represent the actual train or signal.

5.3 Axle detection

Jernbaneverket controls the flow of train traffic in Norway, and given live locations of trains the BWIM algorithm might not need to find axle distances. Instead a query of existing systems could provide axle distances for the pasing train. This could in theory eliminate a source of error in BWIM algorithm. Detecting axle peaks correctly likely requires an optimization type algorithm for a bridge of this type. There might also exist other methods of getting good estimates of axle distances, but the method of doing this through peaks in a strain signal is too susceptible to noise and dynamics. The peak method appears to be a good way to identy train bogies, and maybe even the center position of the bogies, which may be acceptible for some BWIM systems. As mentioned above in section 5.2 it could be possible to optimize the best possble axle distances. With a known influence line for the sensors and bridge, optimizing axle could work very well, but this has not been investigated or tested in this thesis.

5.4 The main challenges of BWIM

There were many challenges identified, solved and failed, during this thesis.

- Noise leading to problems with:
  - Axle detection
  - Alignment of peaks to build system for calculating axle weights.
  - Depending on the chosen method finding the vehicles speed could be subjected to noise.
- Having sufficient calibration vehicles traversing the bridge to find a representative influence line.
- Removing or minimizing dynamic effects in influence lines calculated by the matrix method.
- To identify when the train starts to influence the bridge statically. This might be particular to BWIM for railway bridges, as the rails affects the bridge long before the train is in contact with the bridge. For the case of Lerelva bridge, there is also the special nature of the support closest to the sensor, which is linked with a short span bridge over a one lane road.

5.5 General summary of the master thesis

In section 1.2 there was a list of goals for this thesis, which will now be reviewed.

1. Implement a working BWIM system

The developement of the a simple BWIM program can be called a success, as the program is able to do all that is required, the system is capable of reading and using any sort of strain signal and identifying peaks corresponding to specific axles or at least bogie. The speed of the trains have been identified using a brute force method, also other methods of finding vehicle speed have been developed and tested successfully with the theoretical beam model.

2. Implement methods for calculating the influence lines for an arbitrary bridge

The BWIM system has been implemented with the Matrix method enabling the calculation of influence lines for a strain signal where the properties of the passing train is known. The testing of the Matrix method indicates that it can quite accurately calculate an influence line for any type of signal, and that this influence line along with axle distances and axle weights is able to recreate the signal with very little error. More specifics about the matrix method is mentioned in 5.1. The influence lines have been the main focus of this master thesis, and efforts went into developing alternatives to the linear matrix method. This was done through optimization, and was successful for the theoretical strain signals produced through the beam model, but more complex bridge structures the optimization proved more subjected to the initial guess of the influence line. With optimization there might also exist more than one satisfying solution satisfying tolerance limits for the routhine. When strain signals from Leirelva was was used to test and further develope the Optimization routing it was found that it required special considerations compared to the matrix method which performed no matter the signal complexities. I do however believe that optimization method has the potential to work well for bridges with smaller spans.

3. Identify good practices for building a BWIM system

Through this thesis I have higlighted good and less good aspects of different parts of my own BWIM system. This can hopefully be of use for further developements of BWIM.

4. Analyse how Bridge weigh-in-motion works for a typical Norwegian steel railway bridge, through measurement data from Lerelva bridge

Most of the analysis uses data from the setup at Lerelva bridge, and shows that calculation of influence lines for this type of bridge may involve bigger challenges than for more simple bridge types, like a slab bridge. Even though information of trains axle weights were not obtained, the influence lines used for calculation of axle weight produced consistent results, especially for gross train weight. Therefore there are good grounds to conclude that BWIM will work for railway bridges similar to Lerelva Bridge.

5.6 Possible improvements and suggestions of future work

For future developements and further research on a BWIM system, the sample data gathered from the bridge in question need to be induced by a train or vehicle with known properties. The wanted properties of a calibration vehicle or train:

- Exact velocity of the vehicle or train
- Every axle distance is known.
- The axle weights of the train or veichle is known at the time of traversal.

This would enable the methods for calculating influence lines to be analysed with the main goal of the system, namely calculating axle weights, in mind. The axle weights calculated using the influence lines from the matrix method could then be compared and a proper error area identified.

For identifying how the dynamics of train and bridge affect the BWIM system, and the calculations of influence lines, the trains traversing the bridge at a range of velocities would be of particular use. The results of such a calibration would also give estimates of the best traversal velocities for the bridge in question, which could provide information enabling the elongation of the bridge's lifespan. For reasons of comparison, implementation and testing of a shorter railway bridge in concrete or steel would be interesting. If a second bridge or a shorter span could be found within the same section of a railway, the same train could provide data on two different bridges. This could help identify the limits of a railway BWIM system.

An alternative to the Matrix method could be to use theoretical influence lines for a more complex beam model. For the bridge discussed in this thesis for instance the simple beam model is insufficient, and a model more representative to the system could be like shown in figure 5.1. The influence line found through such a model could be adapted to actual bridge supports, and a good approximation of the actual influence line could be found using optimization routines. A drawback of this way of finding influence lines could be that the bridge model would have to be adapted to each system setup.

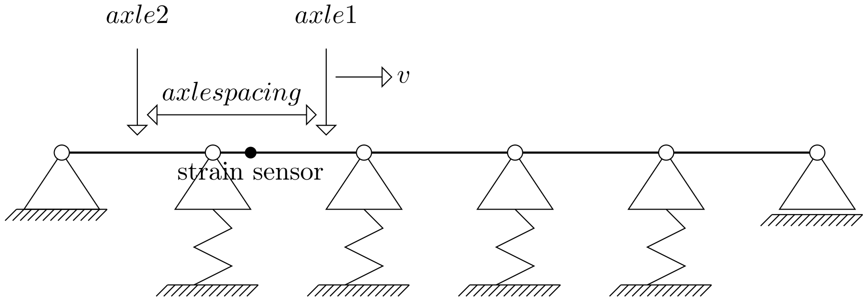


Figure 5.1: A more realistic beam bridge model

I believe that the posibilities of BWIM are numerous and that it can be useful for existing systems and possibly replace them over time. In particular the possibility of analysing how BWIM could be used to estimate how traffic flow over time will influence bridges. Will BWIM be able to identify changing bridge properies over time?

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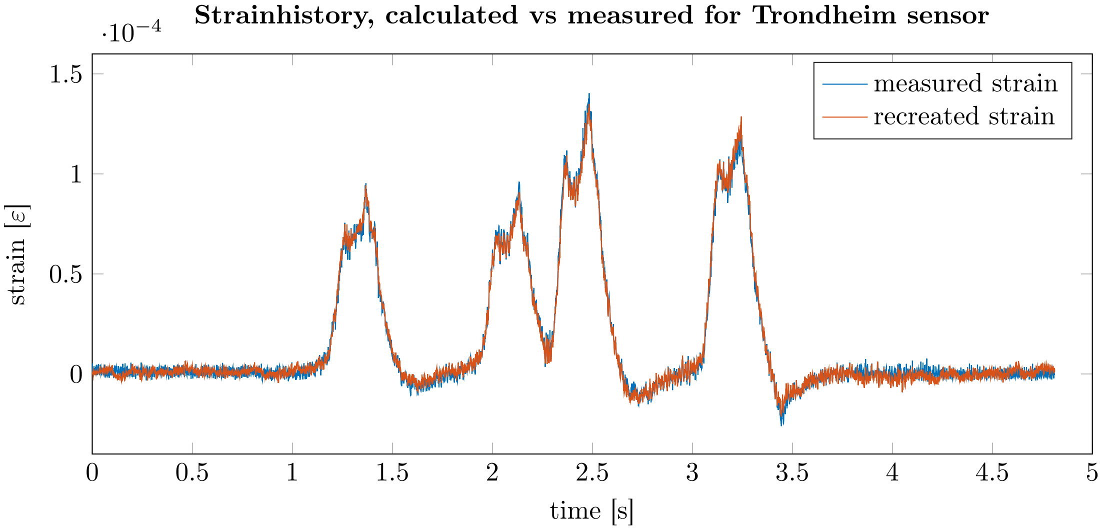
Appendices

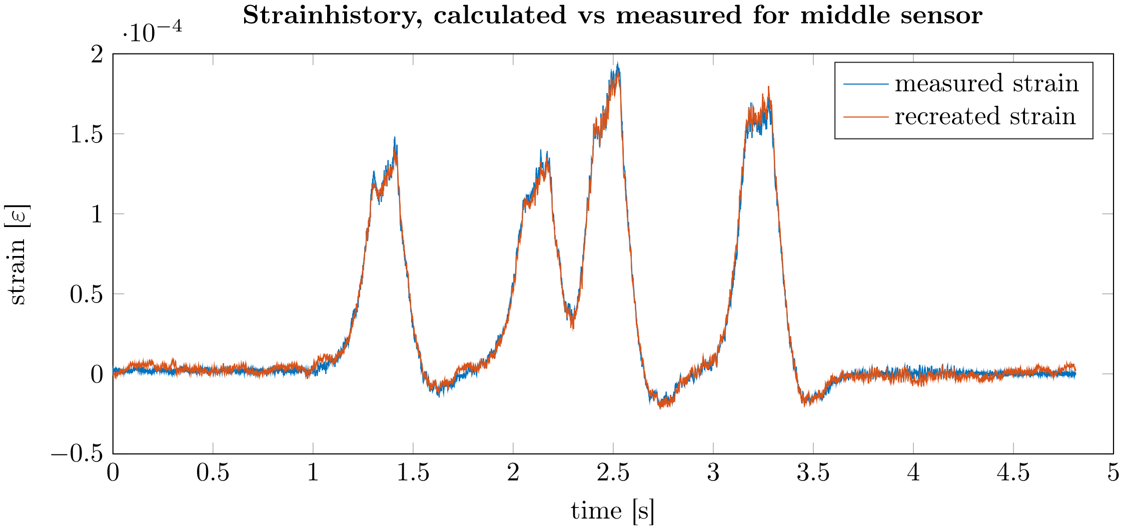
A. Figures

A.1 Recreated strain signals

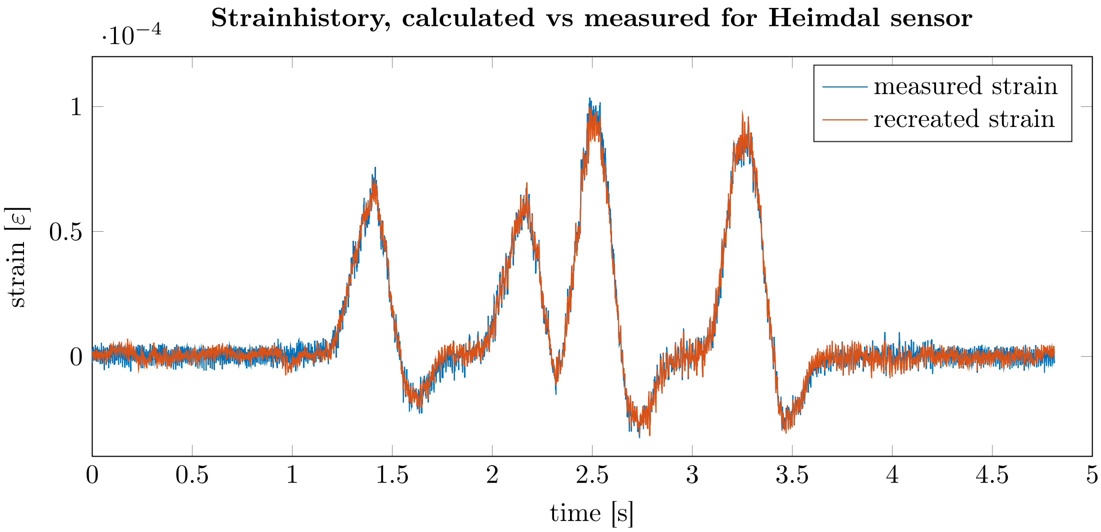
A.2 Influence lines all sensors



(a) Recreated strain, Trondheim sensor, train4

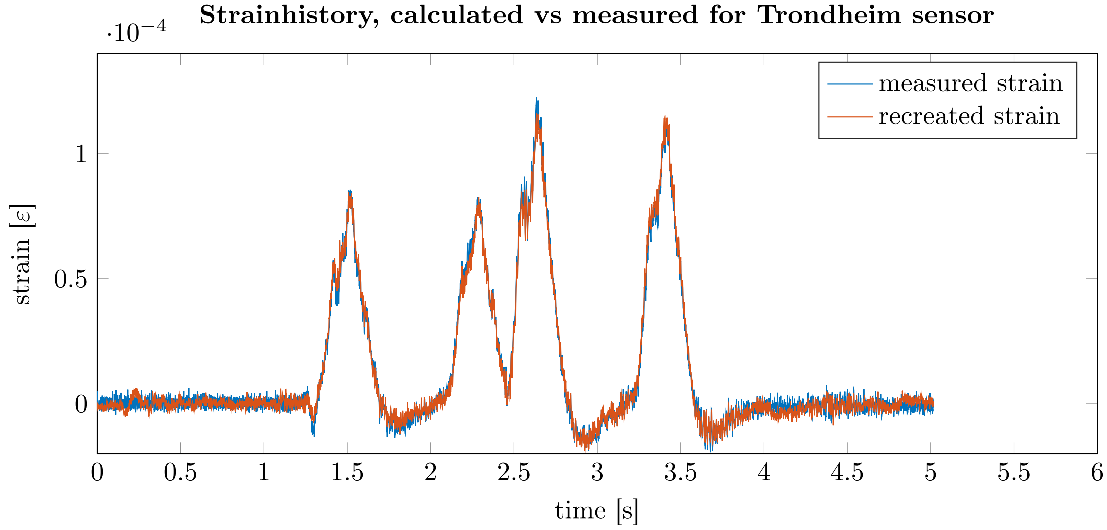


(b) Recreated strain, middle sensor, train4

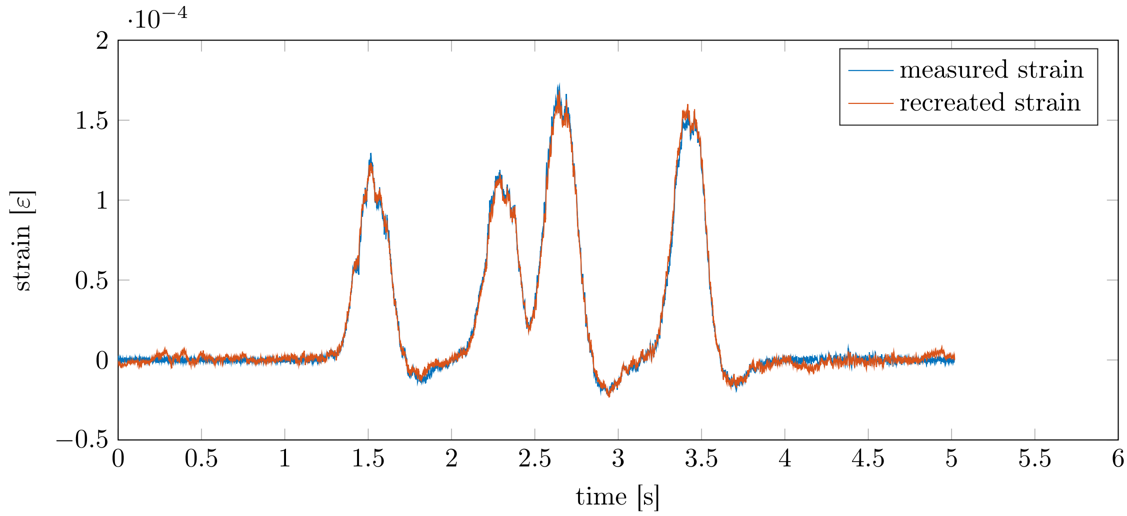


(c) Recreated strain, Heimdal sensor, train4

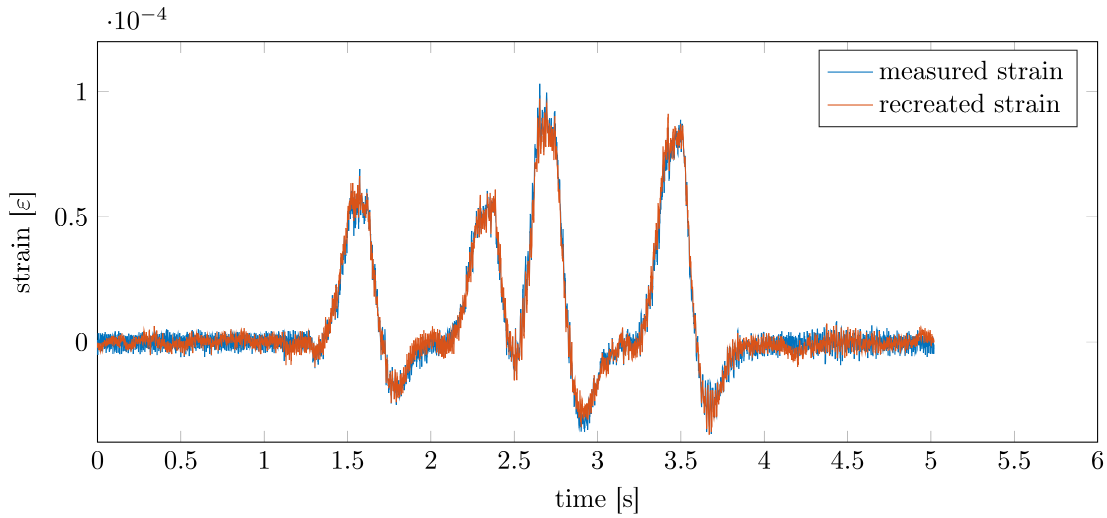
Figure A.1: Recreated strain signals for train 4



(a) Recreated strain, Trondheim sensor, train5

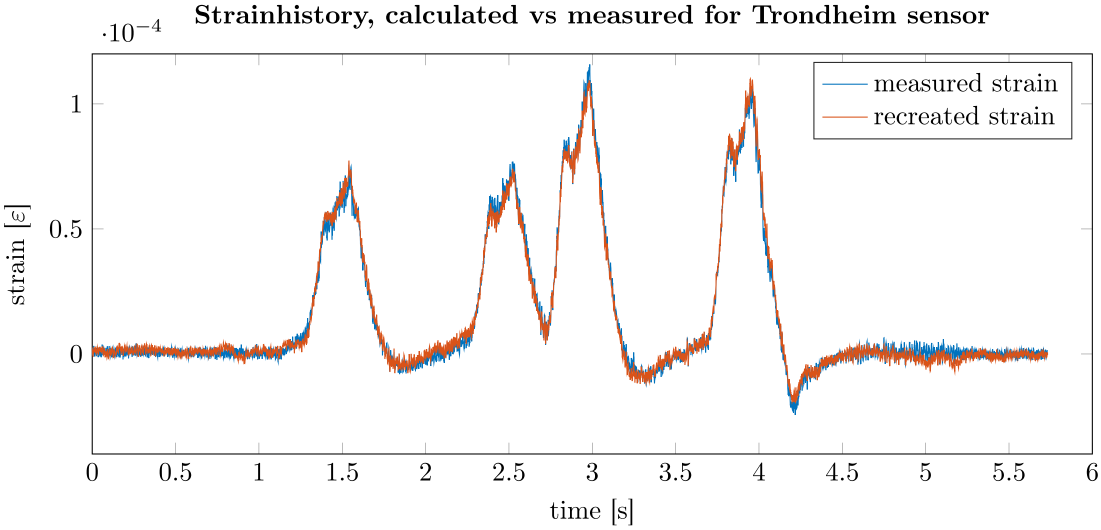


(b) Recreated strain, middle sensor, train5

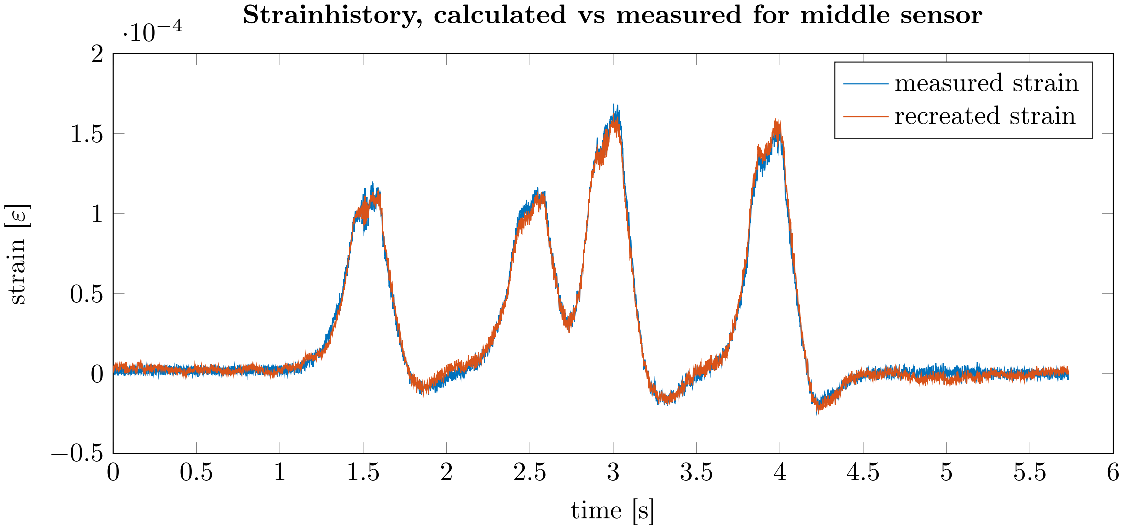


(c) Recreated strain, Heimdal sensor, train5

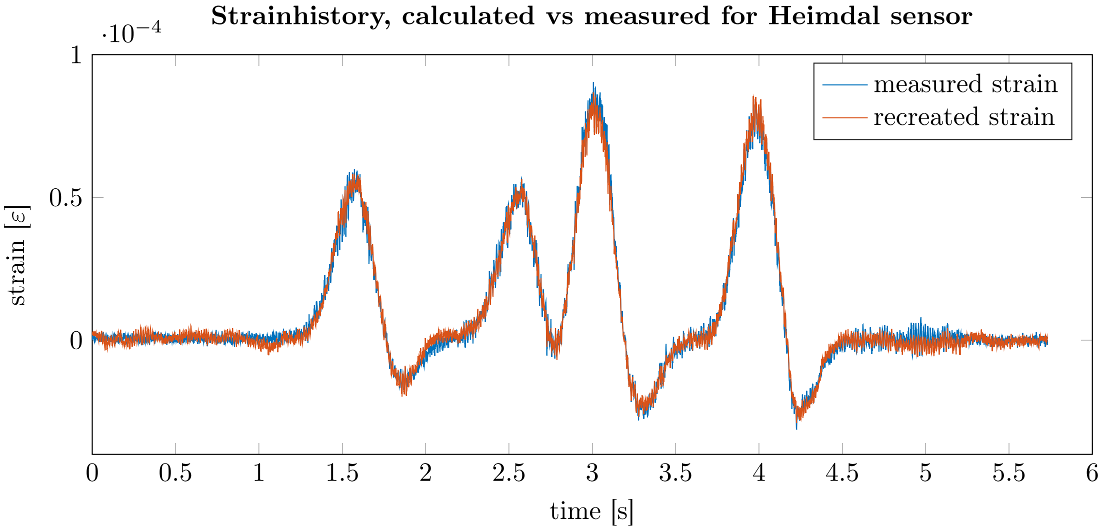
Figure A.2: Recreated strain signals for train 5



(a) Recreated strain, Trondheim sensor, train6

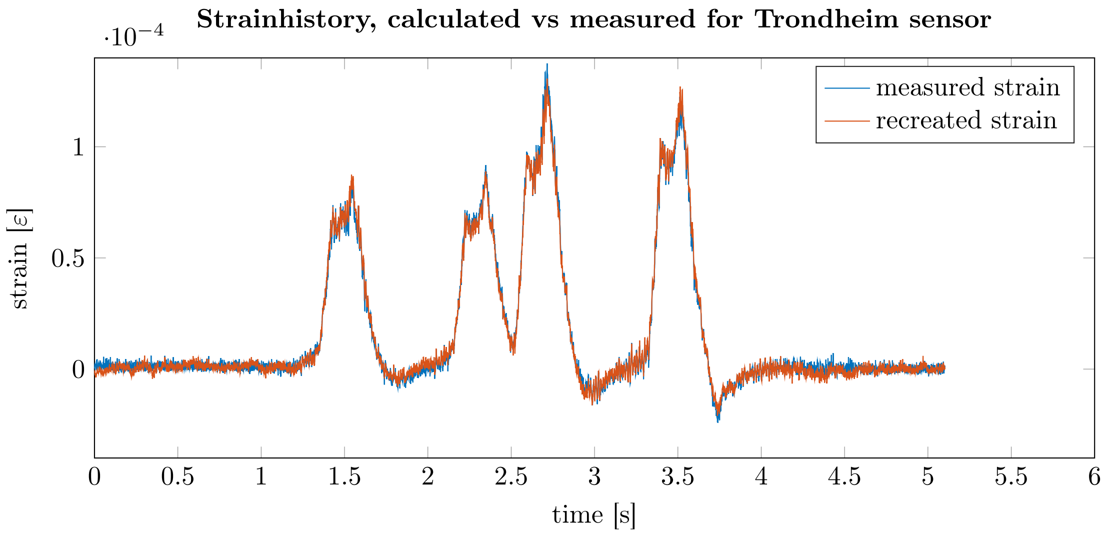


(b) Recreated strain, middle sensor, train6

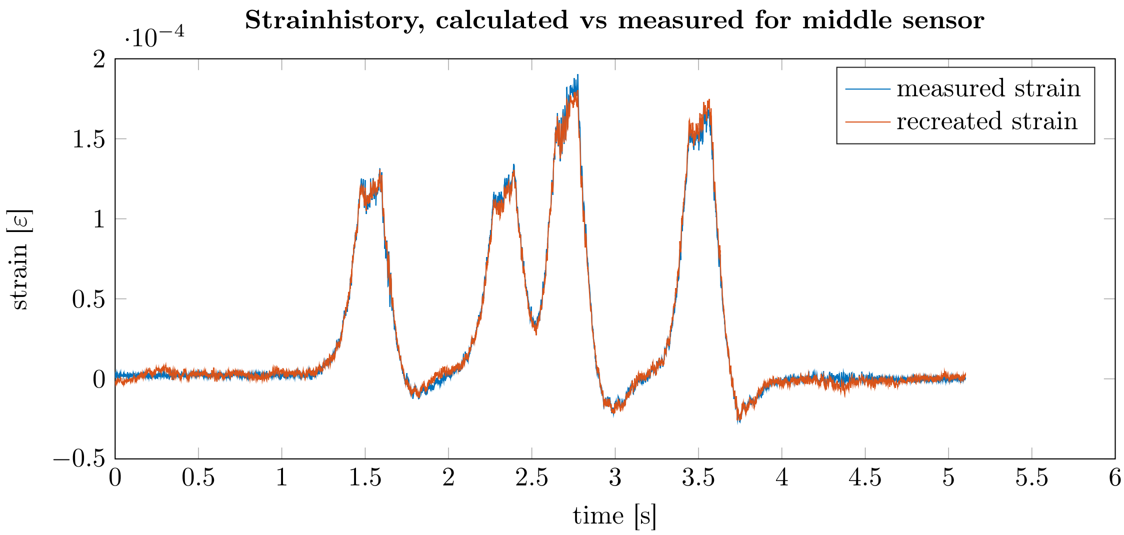


(c) Recreated strain, Heimdal sensor, train6

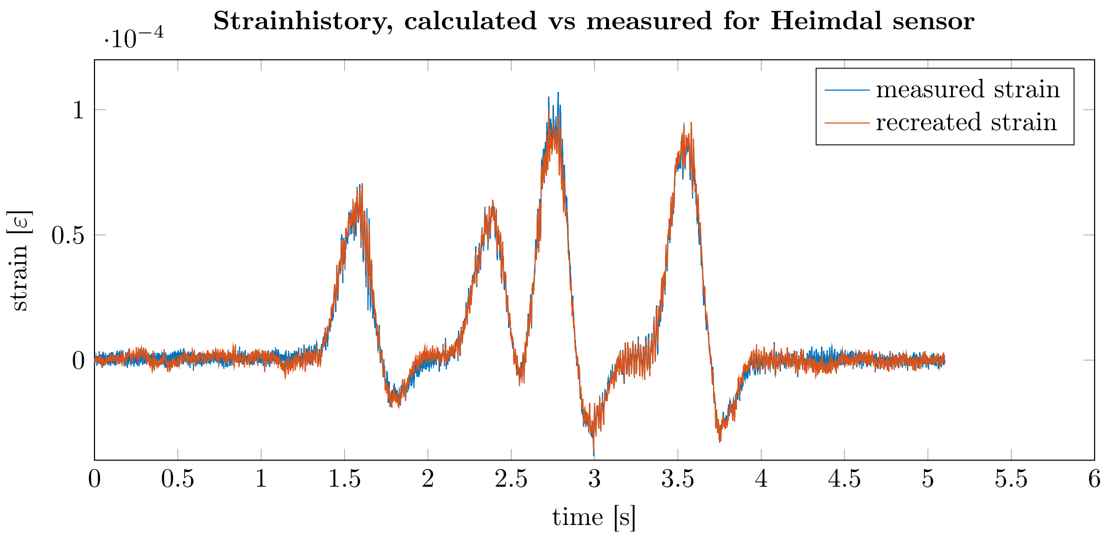
Figure A.3: Recreated strain signals for train 6



(a) Recreated strain, Trondheim sensor, train8

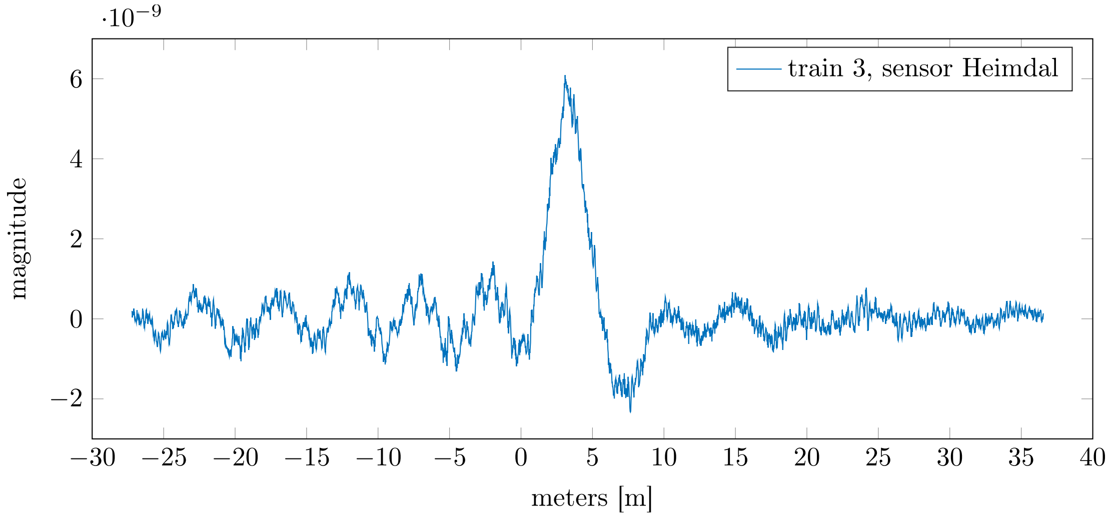


(b) Recreated strain, middle sensor, train8

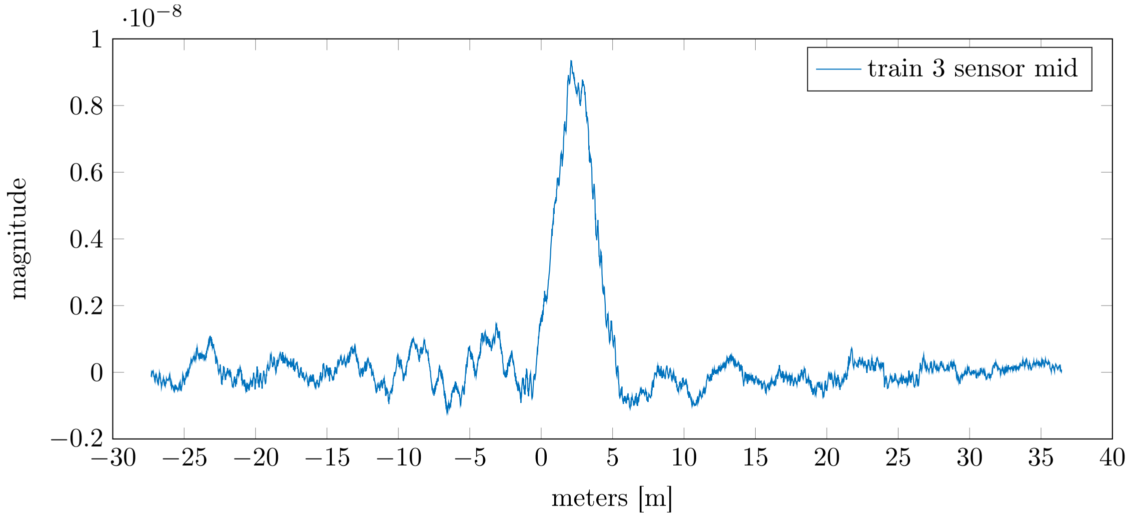


(c) Recreated strain, Heimdal sensor, train8

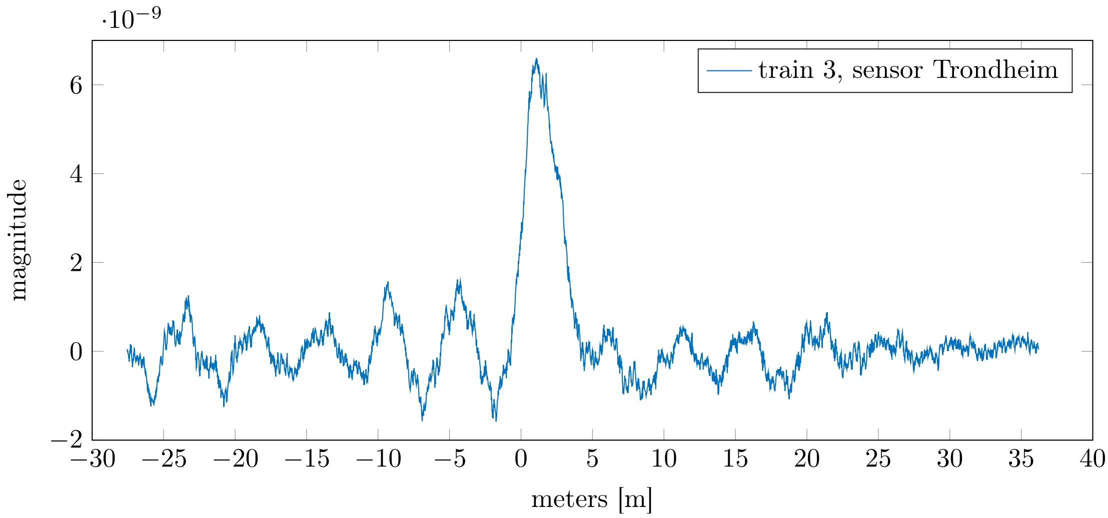
Figure A.4: Recreated strain signals for train 8



(a) Influence line for sensor towards Heimdal, train 3

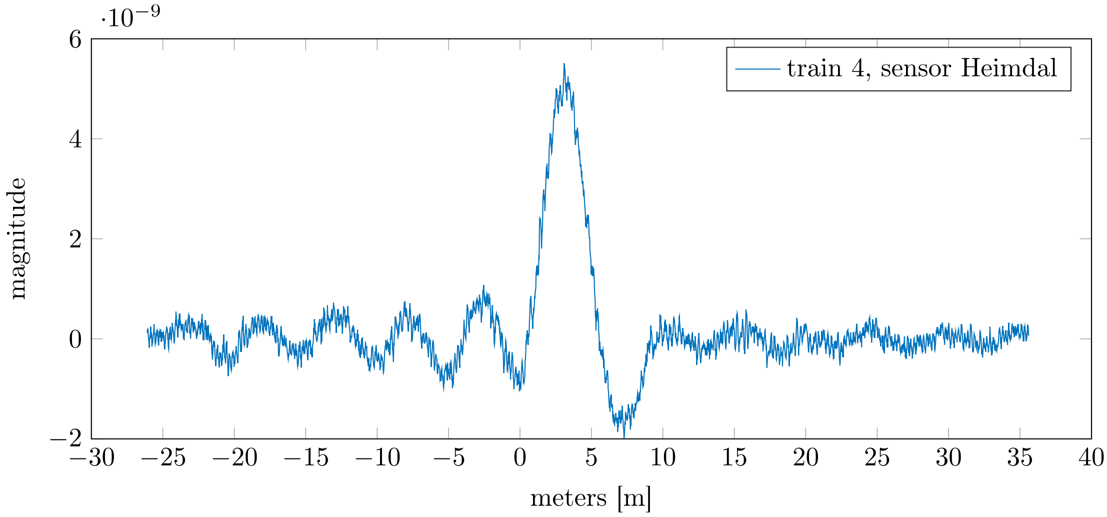


(b) Influence line for middle sensor, train 3

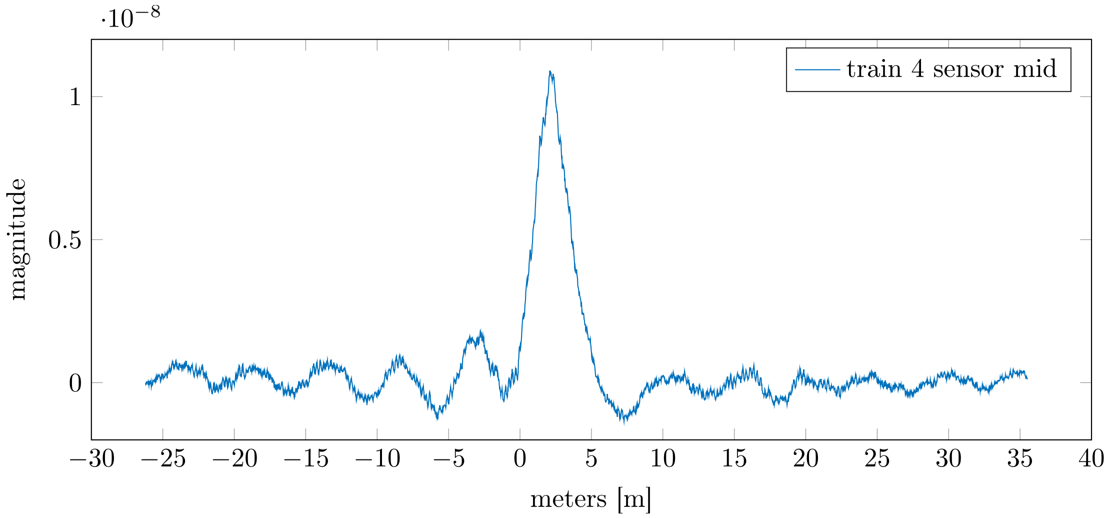


(c) Influence line for sensor closest Trondheim, train 3

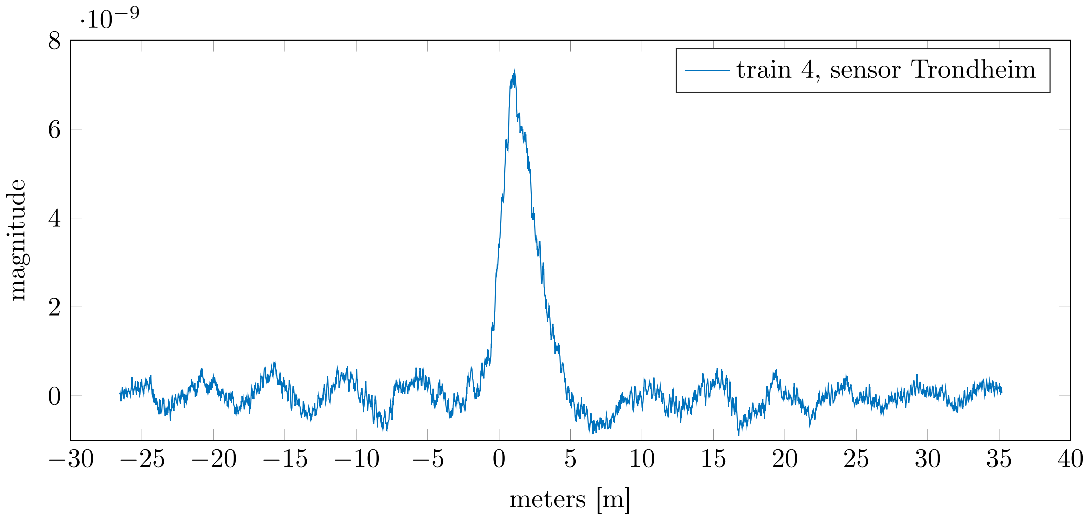
Figure A.5: Influence lines train 3



(a) Influence line for sensor towards Heimdal, train 4

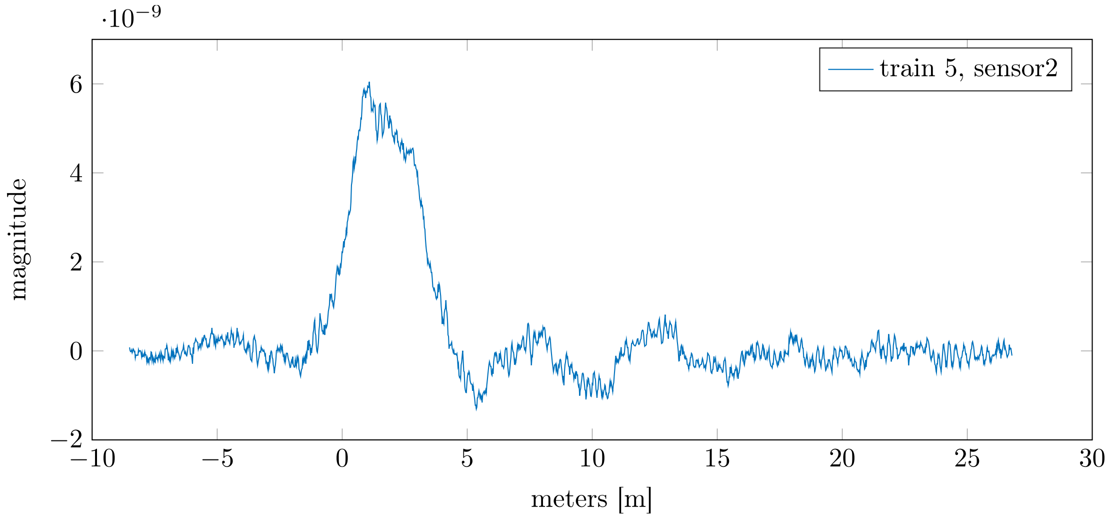


(b) Influence line for middle sensor, train 4

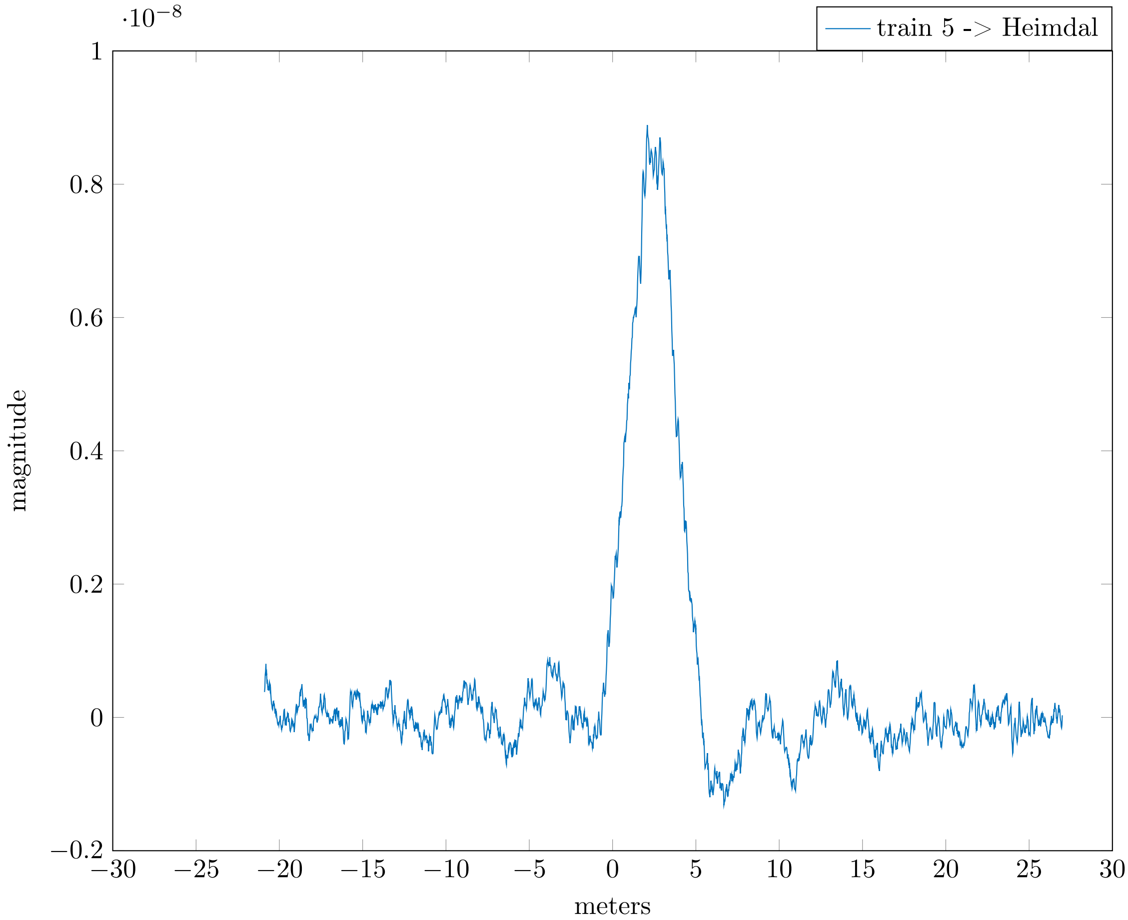


(c) Influence line for sensor closest Trondheim, train 4

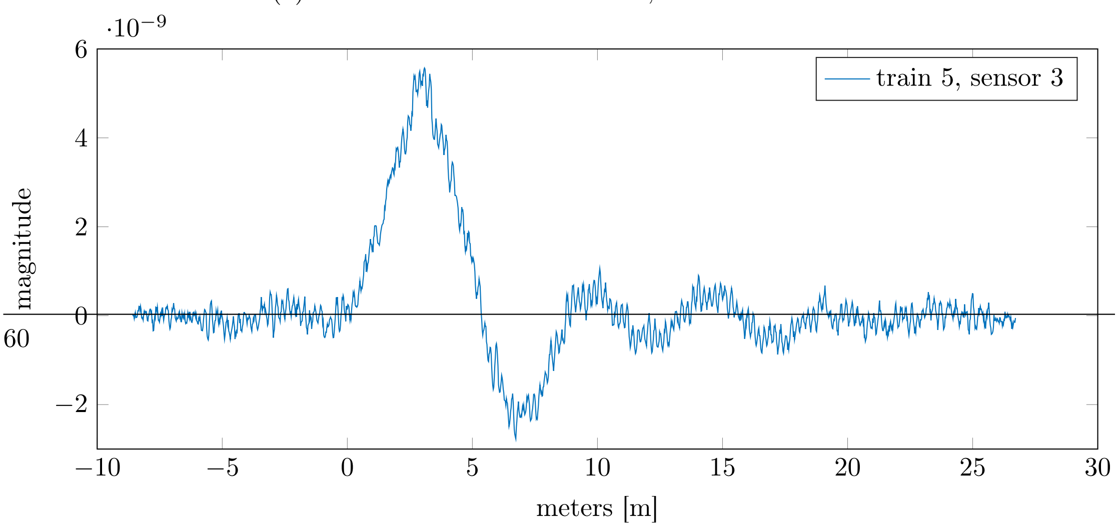
Figure A.6: Influence lines train 4

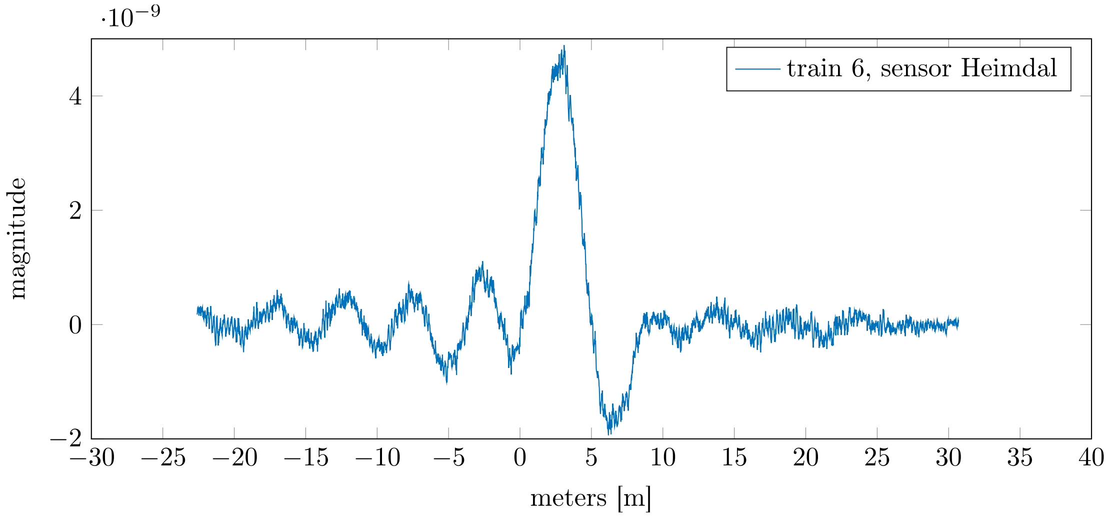


(a) Influence line for sensor towards Heimdal, train 5

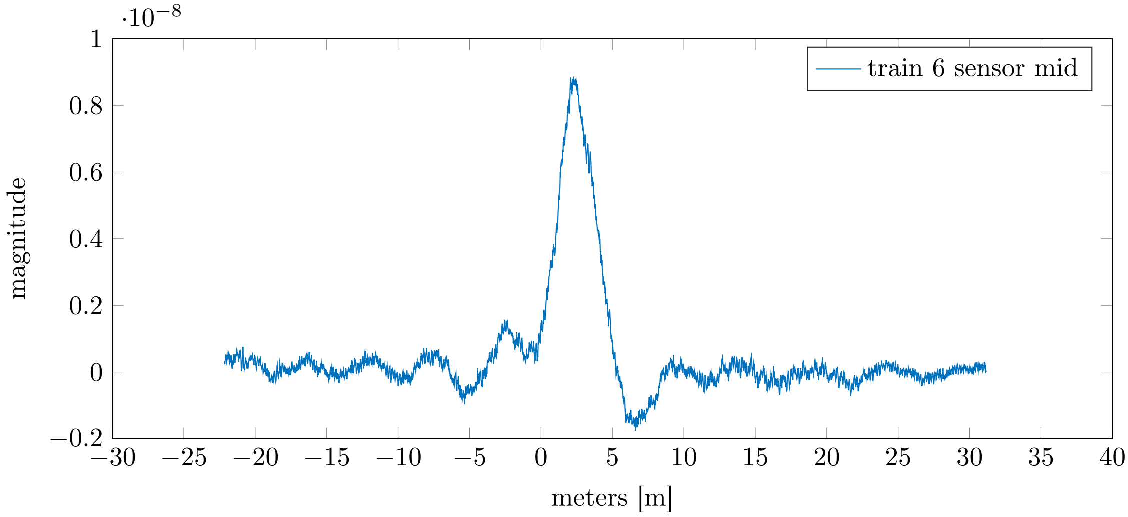


(b) Influence line for middle sensor, train 5

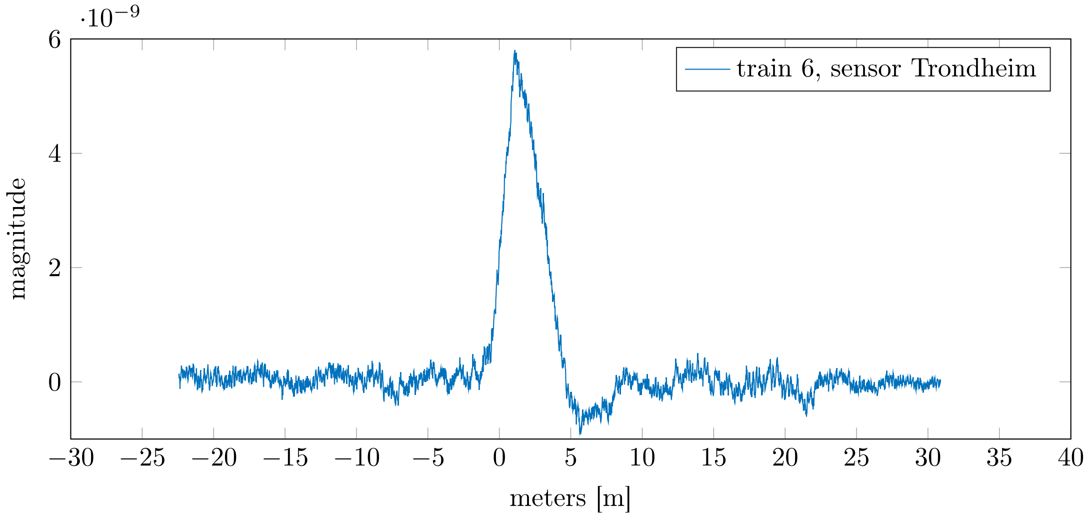




(a) Influence line for sensor towards Heimdal, train 6

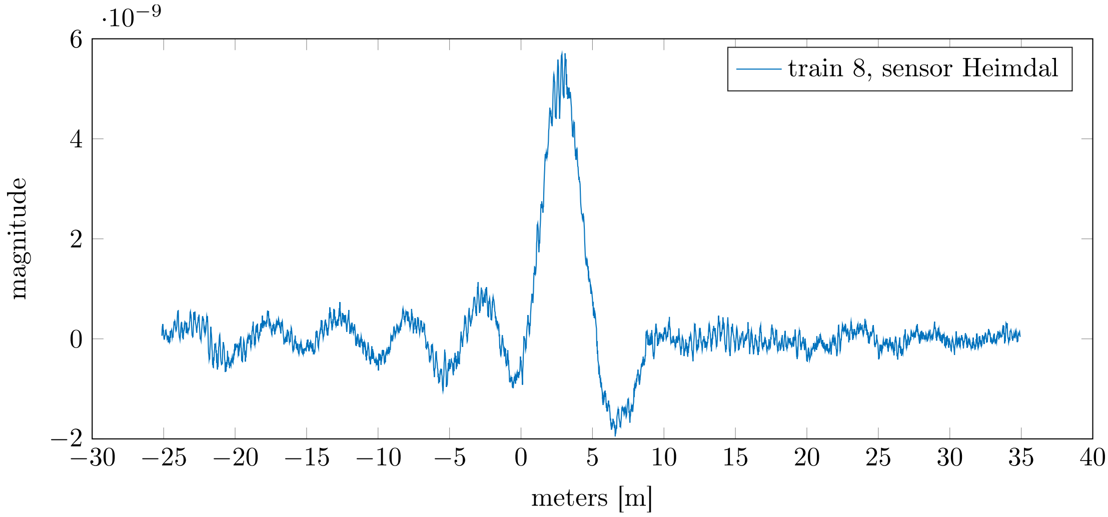


(b) Influence line for middle sensor, train 6

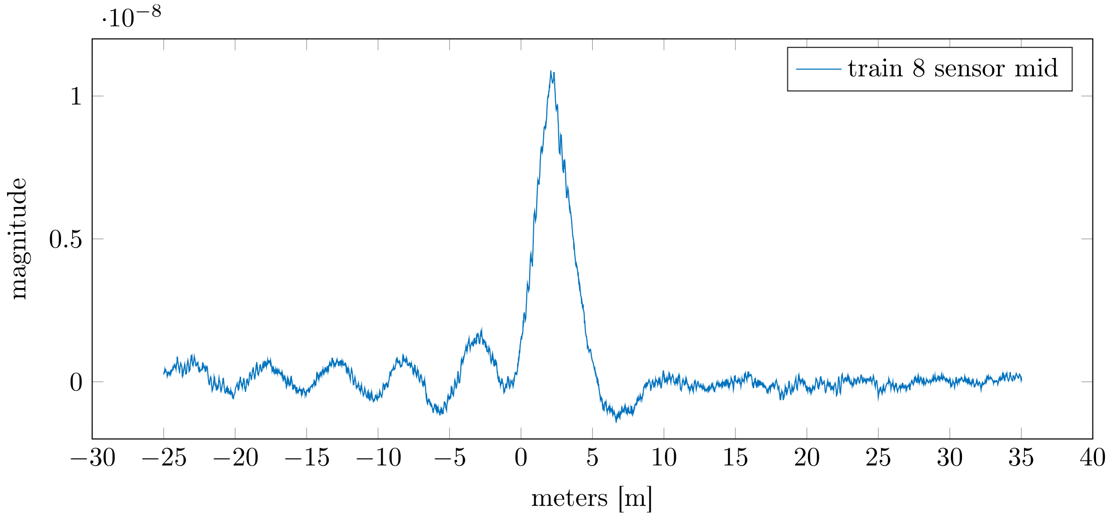


(c) Influence line for sensor closest Trondheim, train 6

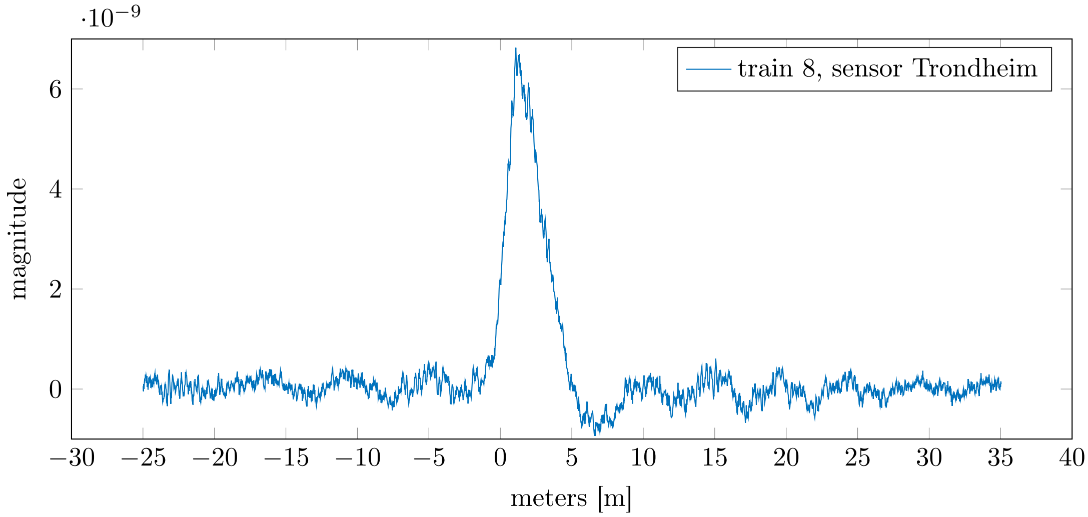
Figure A.8: Influence lines train 6



(a) Influence line for sensor towards Heimdal, train 8



(b) Influence line for middle sensor, train 8



(c) Influence line for sensor closest Trondheim, train 8

Figure A.9: Influence lines train 8

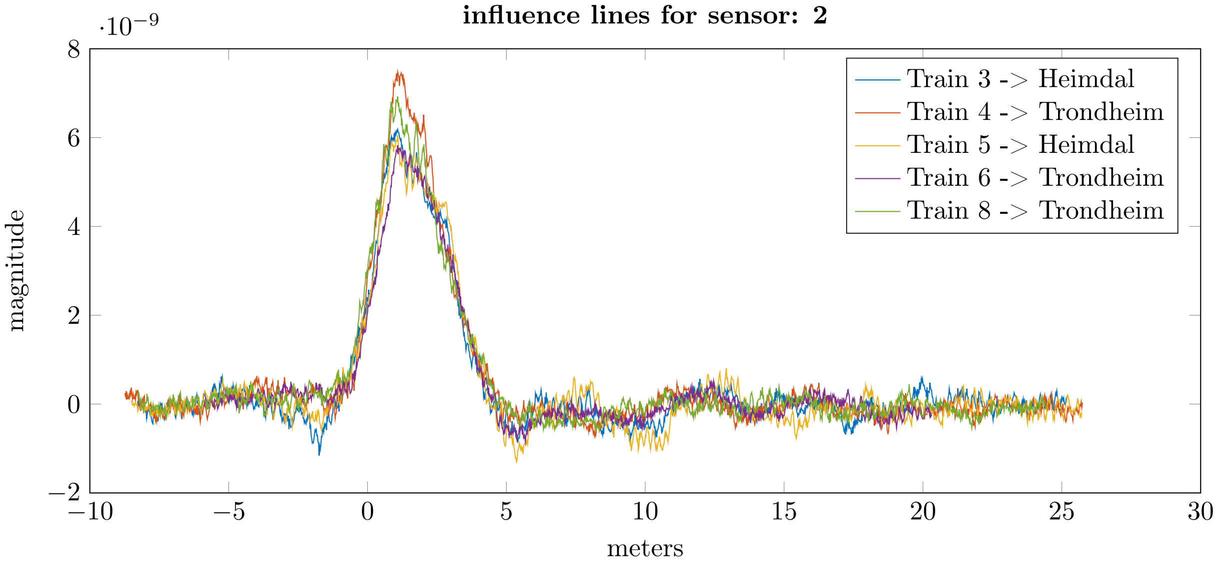


Figure A.10: Influence lines from figure:4.4 on top of each other for sensor 2

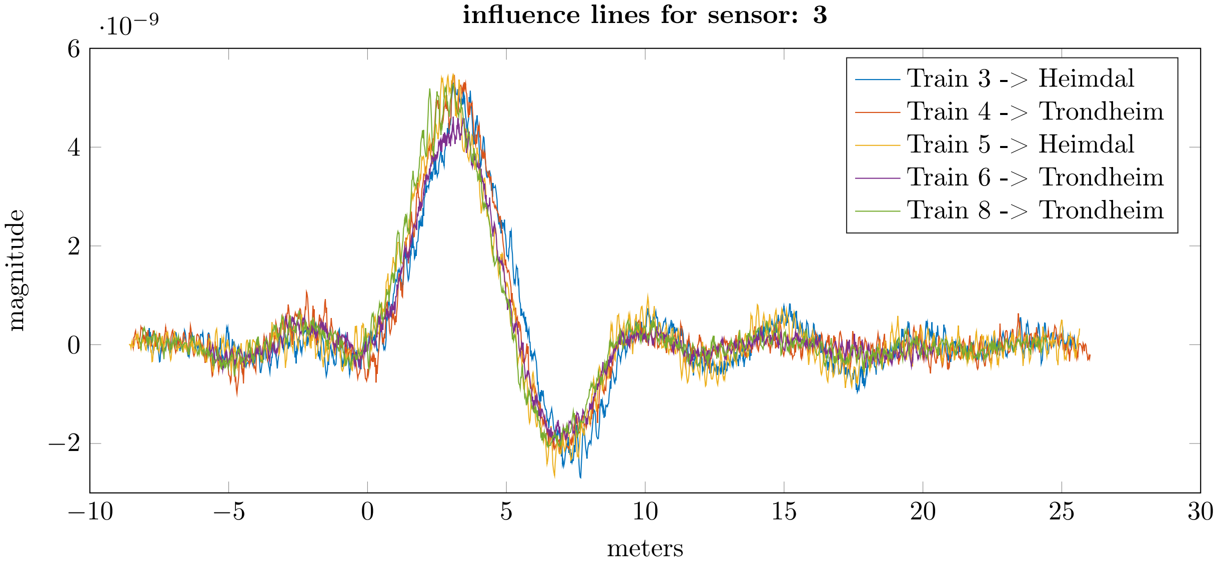


Figure A.11: Influence lines from figure:4.4 on top of each other for sensor 3

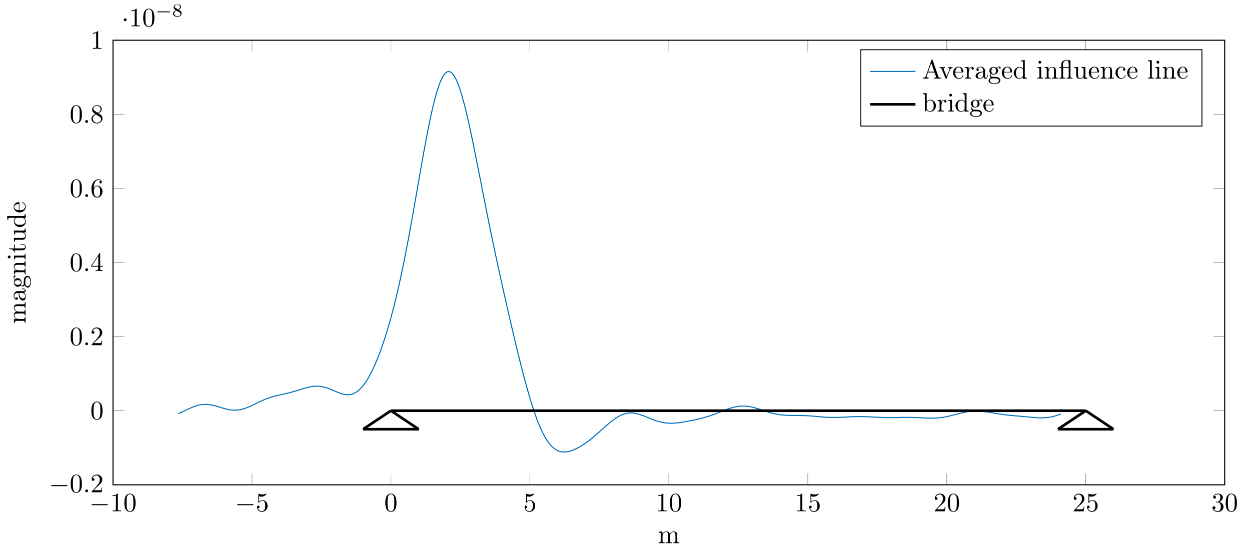


Figure A.12: Averaged influence line for sensor 2

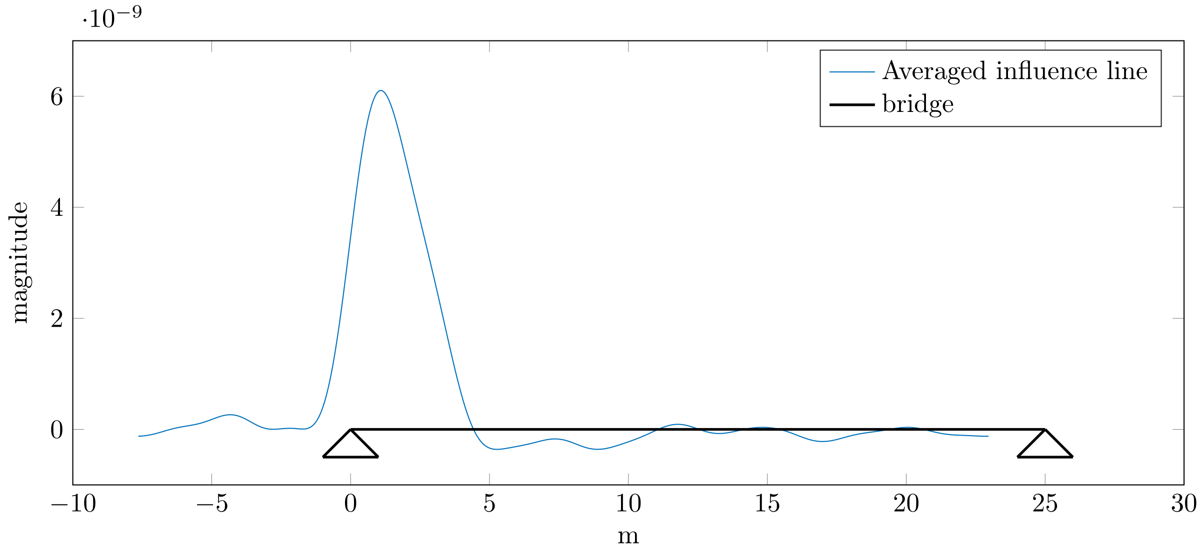


Figure A.13: Averaged influence line for sensor 2

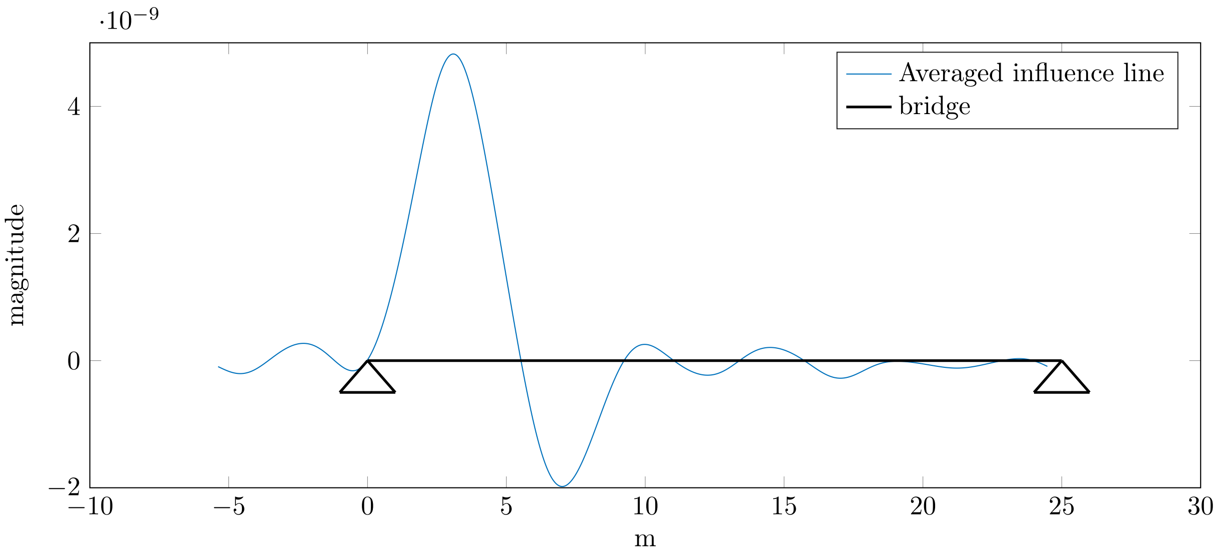


Figure A.14: Averaged influence line for sensor 3

B. Construction drawing of Lerelva bridge

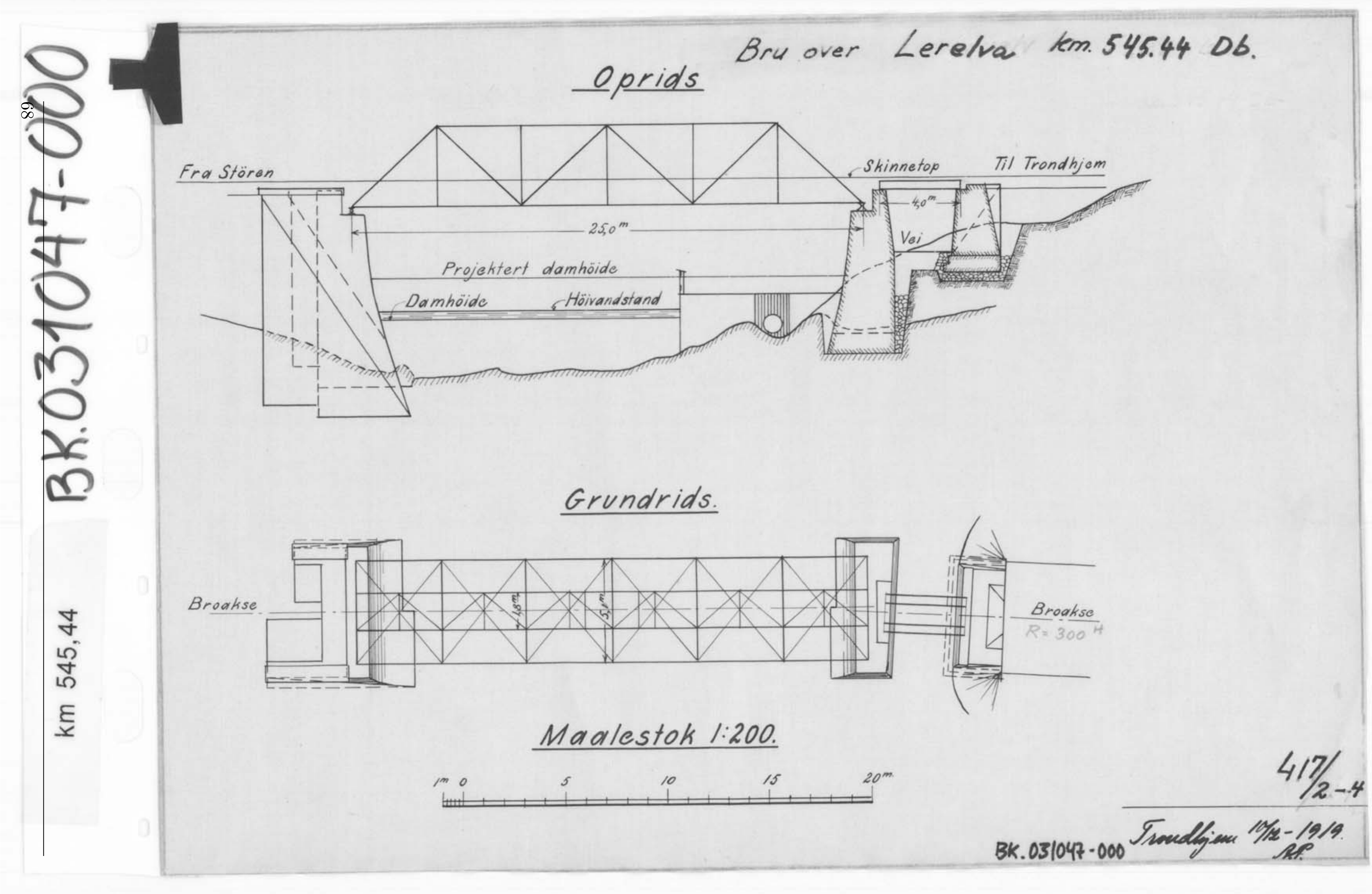


Figure B.1: construction drawing showing general dimensions for lerelva bridge

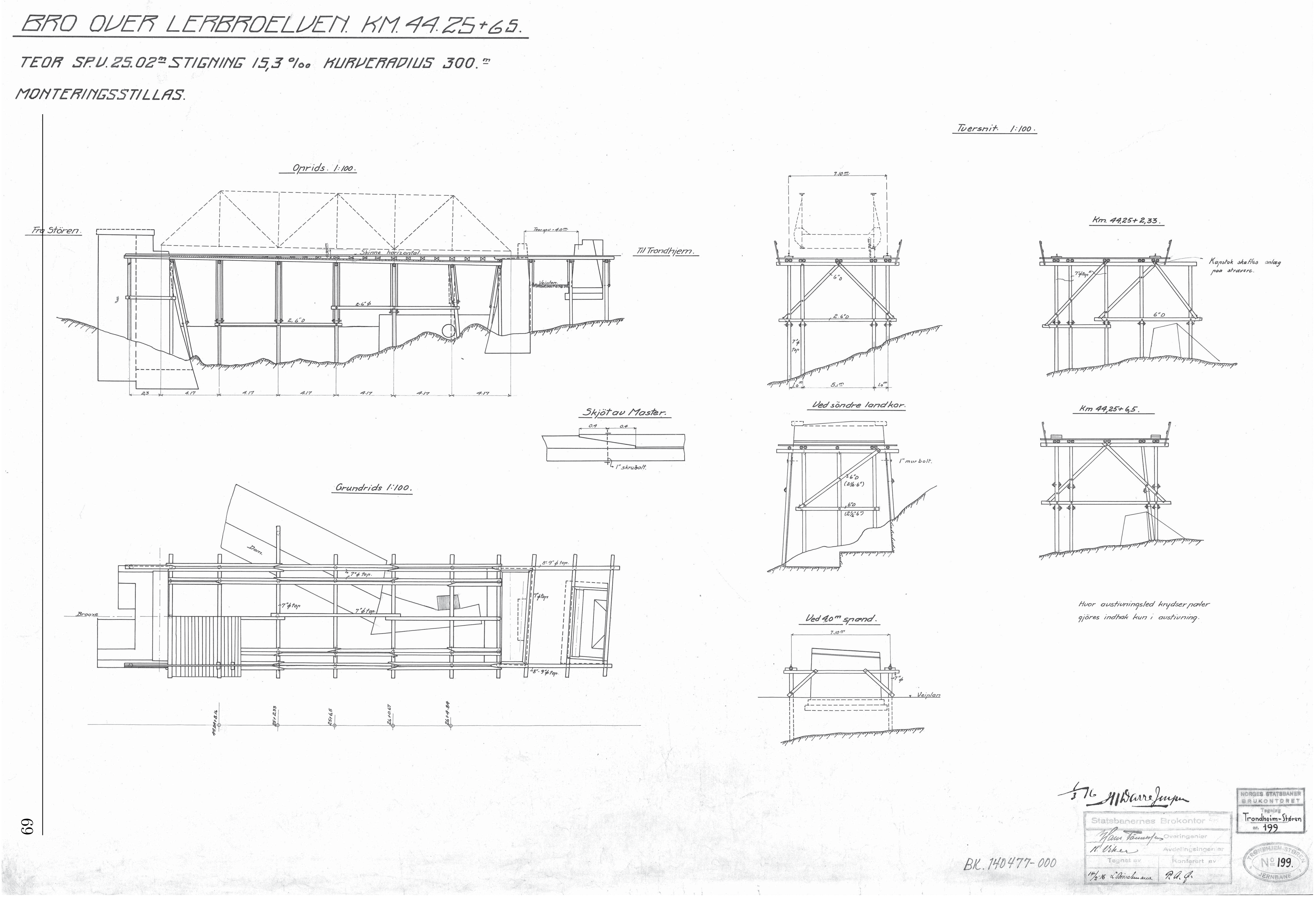


Figure B.2: construction drawing showing section dimensions for lerelva bridge

C. Algorithms and code

```
function [  M_c, A, C ] = findInfluenceLines( strainHistory, TrainData)
% This method will compute the necessary matrices and vectors for solving
% the system giving influence lines for a BWIM system
% This will be acomplished through Moses' equation
% The axle loads [A] are known, so the influence ordinates which minimises
% the following equation give best the best solution
% E = sum_from_k=1_to_k=numOfScans((M_k^M - M_k^T)^2)
% M_k^M = measured strain at scan k - measured response
% M_k^T = theoretical response
% TrainData is a matlab struct containg info of train speed, axle spacings
% and so on
% The returned variables: M_c =  a vector depending on axle weights and measured strain
% A = matrix depending only on axle spacing and axle weights
% C = axle distances in signal samples
format long;
speed = TrainData.speed;
frequency = 1/TrainData.delta;
k = length(strainHistory);
n = length(TrainData.axleWeights); % number of axles
C = zeros(1,n);
% The matrix size

C(1) = 0;
% calculates axle distances in signal samples, depending on sampling frequency and train speed
for i = 1:n-1
        C(i+1) = round((sum(TrainData.axleDistances(1:i)))*frequency/speed);
end
% % Defining the matrix size
if C(length(C)) > k
%    Extract the necessary parts of the C vector
    Cnew = C(C<k);
end
m = k-C(length(C));
M_c = zeros(m, 1);
for i = 1:m
    for j = 1:n
        M_c(i,1) = M_c(i,1) + TrainData.axleWeights(j)*strainHistory(i+C(j));
    end
end

% Now creating the A matrix, which depends on the axle weights
% The diagonal <-> sum of the squares of the axle weights
% The loop only calculates the upper triange of the matrix
A = zeros(m, m);

for i = 1:n
    for j = i:n
```

```
        offset = C(j)-C(i);
                if((m) - abs(offset))>0 % axle n does influence strain
            oneVec = ones(1,m - abs(offset));
            diagonal = diag(oneVec,offset);
            A = A + TrainData.axleWeights(i)*TrainData.axleWeights(j)*diagonal;
        end
    end
end
% Form the full matrix through the transpose of the upper triangle
A = A + tril(transpose(A),-1);
end
```