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# A Time-Dependent and Parametrical Assessment of Weigh-in-Motion Data

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**Abstract:** Weigh-in-motion (WIM) systems measure the weight of moving vehicles. In Norway, WIM is used for speed limit enforcement, but it can also be used to estimate vehicle weights. The aim of this thesis was to evaluate how data from Weigh-in-Motion systems (WIM) could be used for road and traffic engineering purposes. Using such weight data can provide better statistics for road planners and authorities. This can subsequently be used for designing new roads and calculating road wear.

The methods involved comparing WIM weights and corresponding static weights of heavy vehicles to see how similar they were. This was done at several WIM sites. In addition to this, it was examined if the discrepancy increased over time. Statistical analyses helped to evaluate if the differences were significant or not.

The results showed that WIM generally underestimated the static weights, causing large errors up to - 40 % for gross weights. This error seemed to be systematic (linear), which caused larger errors for heavier vehicles. Further, the errors from one WIM site increased over time. This was partly caused by a higher mean static weight that lead to increasing errors due to the systematic error. Unrepresentative vehicle samples, which lead to different static weights at separate days, seemed to be causing this. Other factors such as road surface integrity, composition and design were also thought to influence the errors.

Moreover, it was shown that the errors of gross vehicle weights were more similar than those from the front axle weight or the weight of other axle combinations. But as a result, the WIM data was shown to have adequate accuracy for acquiring statistics that can be used for road planning purposes. Further, by adjusting the WIM weights with several calibration coefficients, the accuracy classes generally improved.

**Keywords:**

1. Weigh-in-motion
2. Data quality assessment
3. Weigh-in-motion calibration
4. Accuracy classes



## Preface

This Master's thesis is part of the subject TBA4945 Transport vår 2016 at the Civil and Environmental Engineering study programme at the Norwegian University of Science and Technology (NTNU) in Trondheim, Norway.

The task's subject was proposed by the Norwegian Public Roads Administration (NPRA), and what made this subject catch my attention was its need for data acquisition, statistical analysis and learning more about several types of sensors and road systems that are used all over Norway.

In this thesis, I will look at how data from weigh-in-motion systems can be used to more purposes than just speed limit enforcement. Examples are using the data for road design, examining axle loads restrictions and calculating road wear. This can subsequently help the NPRA by increasing their knowledge of such systems and helping them make better decisions.



## Acknowledgements

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However, my greatest thanks go to my supervisor, Torbjørn Haugen, for proof-reading this thesis, giving me advice about this task, organising the data acquisitions and a lot more. Without him, this task would have been a lot more difficult to accomplish.

Timothy Pedersen



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## Sammendrag

Denne mastergraden handler om Weigh-in-Motion-systemers (WIM) bruksområder for vei- og trafikkingeniørfag. I Norge brukes WIM til fartskontroll, men det kan også brukes til å estimere kjøretøyvekt. Bruk av slik data kan gi bedre statistikk for veiplanleggere og veimyndigheter. Dette kan brukes til dimensjonering av nye veier og for å anslå veislitasje.

Data fra WIM kan klassifiseres i forskjellige nøyaktighetsklasser, som hver har ulike bruksområder. Dette gjør det mulig for oss å vite hvordan våre WIM-data kan brukes.

Metodene omhandler sammenlikning av WIM-vekter og de korresponderende statiske vektene for å se hvor like de er. Dette gjøres på flere WIM-punkter. I tillegg til dette har det blitt undersøkt om ulikhetene øker over tid. Statistiske analyser har hjulpet for å bestemme om forskjellene er signifikante eller ikke.

Resultatene viser at WIM generelt sett underestimerer de statiske vektene, noe som fører store feil opp mot - 40 %. Denne feilen synes å være systematisk (lineær), som skaper større feil for tyngre kjøretøy. I tillegg øker feilen fra ett WIM-punkt over tid. Dette stammer trolig fra ikkerepresentative kjøretøyutvalg som fører til forskjellige statiske vekter på ulike dager. Andre faktorer som veioverflateintegritet, -sammensetning og -design tenkes også å påvirke feilen. Videre har det blitt vist at feilen ved totalvekter er likere enn den fra frontakselvekten eller vekten fra andre akselkombinasjoner. Som et resultat har WIM-dataene blitt vist til å være tilstrekkelig for å ta statistikk som kan brukes i veiplanleggingsformål. Ved å justere WIM-vektene med ulike kalibrasjonskoeffisienter, så har nøyaktighetsklassene generelt forbedret seg.



## Summary

This master's thesis is about Weigh-in-Motion (WIM) systems' applications for road and traffic engineering. In Norway, WIM is used for speed limit enforcement, but it can also be used to estimate vehicle weights. Using such weight data can provide better statistics for road planners and authorities. This can be used for designing of new roads and assessing road wear.

Data from WIM can be classified into different accuracy classes, each of which have several areas of application. This enables us to know how our WIM data can be used.

The methods involve comparing WIM weights and corresponding static weights of vehicles to see how similar they are. This is done at several WIM sites. In addition to this, it has examined if the disparities increase over time. Statistical analyses have helped to evaluate if the differences are significant or not.

The results show that WIM generally underestimates the static weights, causing large errors up to - 40 % for gross weights. This error seems to be systematic (linear), which causes larger errors for heavier vehicles. Further, the error from one WIM site increases over time. This is partly caused by a higher mean static weight that leads to increasing errors due to a systematic error. Unrepresentative vehicle samples, which lead to different static weights at separate days, seem to be causing this. Other factors such as road surface integrity, composition and design are also thought to influence the errors. Moreover, it has been shown that the errors of gross vehicle weights are more similar than those from the front axle weight or the weight of other axle combinations. As a result, the WIM data has been shown to be adequate for acquiring statistics that can be used for road planning purposes. By adjusting the WIM weights with several calibration coefficients, the accuracy classes have in general improved.



## General definitions and explanations

**Weigh-in-Motion (WIM):** “The process of estimating a moving vehicle’s gross weight and the proportion of that weight that is carried by each wheel, axle, or axle group, or combination thereof, by measurement and analysis of dynamic tire forces”<sup>1</sup>

**High-speed WIM (HS-WIM):** “High-speed systems that will operate at speeds ranging from 10 mph to 80 mph and will be primarily used for collecting data about vehicles traveling on highways. They will not require a high accuracy, axles weight may vary between 15 and 20 %. Nowadays, the technology currently used is the piezoelectric sensor, which offers both competitive cost and ease of use”<sup>2</sup> (10 mph = 16,1 km/h, 80 mph = 128,7 km/h)

**Low-speed WIM (LS-WIM):** “Slow-speed systems that will operate at speeds less than 5 mph and will have an accuracy better than 1 %”<sup>2</sup> (5 mph = 8,1 km)

**Measurement accuracy:** “Closeness of agreement between a measured quantity value and a true quantity value of a measurand”<sup>3</sup>

In other words, if the accuracy is high, the value that we are trying to measure will be close to the real value.

**Measurement precision:** “Closeness of agreement between indications or measured quantity values obtained by replicate measurements on the same or similar objects under specified conditions”<sup>4</sup>

**Dynamic vehicle tyre force:** “The component of the time-varying force applied perpendicularly to the road surface by the tyre(s) on a wheel of a moving vehicle”<sup>5</sup>

Also denoted as “dynamic load” or “dynamic weight” is this thesis.

**Static load:** “The weight of a single stationary body or the combined weights of all stationary bodies in a structure, such as the load of a stationary vehicle on a roadway”<sup>6</sup>

**Heavy vehicles:** Vehicles weighing more than 3,5 tonnes.

**Traffic Enforcement Camera (TEC):** Cameras that control the velocity of passing vehicles. If the velocity is too high, the camera takes a picture and the police can give the driver a fine.<sup>7</sup>

**Tractor:** “A short motor vehicle with a powerful engine and a driver’s cab, used to pull a trailer, as in an articulated lorry”<sup>8</sup>

**Semi-trailer:** “A semi-trailer is a trailer without a front axle. A large proportion of its weight is supported either by a road tractor or by a detachable front axle assembly called a dolly”<sup>9</sup>

**Articulated vehicle:** “A large vehicle (esp. a lorry) made in two separate sections, a tractor and a trailer, connected by a pivoted bar”<sup>10</sup>



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## 1. Introduction

For a long time traffic and road engineers have sought after a method to acquire weight data from vehicles without disturbing and delaying traffic.<sup>11</sup> Traditionally, using static weights from weight control sites can provide this data, but it requires a lot of time and staff to be performed. Vehicles have to be selected and intercepted from the road, the static weighing operation has to be performed and violators have to be fined. Subsequently, when many trucks are controlled at once, queues in the weighing area start to build up. This can create delays of 10 to 30 mins for trucks drivers, and as a consequence, drivers who comply with the regulations are penalised by the delays. For these reasons, some form of partially automatic weighing system that measures the weight while vehicles are in motion on the road is highly demanded.<sup>12</sup>

Weigh-in-motion (WIM) are systems that can be used for such purposes. WIM has load sensors that register axle weights of passing vehicles, to which a corresponding timestamp is registered. This enables calculations of vehicle speed, gross vehicle weight (GVW) and axle distances. WIM thus increases the efficiency of weighing vehicles, as trucks no longer need to be stopped and measured on static loads at low speeds.<sup>13</sup>

High-speed WIM measures vehicles when they are traveling at normal speeds. It is fully automated and can record all vehicles passing the sensors. Thus, large amounts of weight data can be collected quickly and efficiently. Such data can examine the amount of overweight vehicles, which subsequently can be utilised to assess road wear and traffic safety,<sup>14</sup> as well as giving input data to transport analysis models and traffic engineering.<sup>15</sup> In the recent years, studies have shown that WIM have lead to a shift towards loading lorries within legal limits, something that's creating a fairer competition between transport firms that are driving with legal loads and those who are not. The systems can also used to estimate emissions from vehicles.<sup>16</sup>

In Norway, WIM systems have piezoelectric cables (pressure sensors) that are used mainly for speed limit enforcement. By using a known spacing of 3 m between two piezoelectric cables, the velocity at one site can be calculated when the time difference is taken into account. Another form of speed limit enforcement, section control traffic enforcement cameras (S-TEC), measure the average velocity between two TEC sites over a distance of several kilometres. However, in neighbouring countries like Sweden, cameras and radars are used for speed limit enforcement instead of weigh-in-motion systems.<sup>17</sup>

Due to the wide focus on using WIM for speed limit enforcement in Norway, weight data becomes a byproduct from TECs that can be used. The following three needs have lead to an increased demand after WIM data in Norway:<sup>18</sup>

- 1) Pre-screening vehicles in order to statically weigh vehicles that might be overloaded.
- 2) Acquire better statistics over vehicle composition concerning the design of new roads and estimating road deterioration. Road wear is proportional to the vehicle weight raised to the power of four and has therefore a big impact on the road infrastructure.
- 3) Acquire weight data from roads with limited allowed axle loads, such as bridges, to see if the regulations are being complied.

Obtaining more and better statistics about vehicle weights therefore has a wide extent of applications that can be useful for the road authorities. It can save a lot of money by avoiding inefficient static weighing. Furthermore, it would also exploit the existing infrastructure at a larger extent and thus remove the need for establishing new WIM sites.

Therefore, we want to examine how good the data from such WIM systems is and how it can be used to reduce the three above-mentioned needs for WIM data. By using several statistical methods, we will be able to see how accurate the data is and whether it can be beneficial or not for the road authorities for such purposes.

## 1.1.State of the art

Finding previous research papers about similar topics is important as it gives information to the researcher about what has already been done. In addition to this, certain methods can already have been created, thus saving the researcher time.

Weigh-in-motion is a broad field of studies and by searching through online libraries, attending an ITS conference and having my supervisor to give me relevant papers, I have found three reports that are very relevant to my topic.

One is written by the researchers Mr. van Loo and Mr. Lees, who combined have many decades of experience with weigh-in-motion systems. The second report is written by a former student intern at NPRA, who analysed WIM data from one site by using methods from the reputable European WIM standard COST 323. The last report is a project work by former master's student Erlend Aakre and is about the quality of WIM data and methods for improving the accuracy. Below is a more thorough description of the three reports:

### Standard quality checks

Loo & Lees (2015) write in their paper *Standard quality checks for weigh-in-motion data*<sup>19</sup> that variable quality of WIM data makes certain research papers conclude on faulty data. They state that this is problematic and that a standard method for assessing the data quality is needed. In their report, they have proposed four tests and criteria to make a verification of the data quality (quotation from the report. Definitions are listed in a previous chapter):

- 1) *The vehicle length of Truck + Trailer combinations and that of Tractor + Semi-trailer (articulated) combinations. For most EU member states the maximum allowable lengths for these combinations are respectively 18,75 m and 16,50 m;*
- 2) *The Gross Vehicle Weight (GVW) of 3 axle Trucks and that of 5 axle Tractor + Semi-trailer (articulated) combinations. For most EU member states the maximum allowable GVW's for these combinations are respectively 26 tonnes and 40/44 tonnes;*
- 3) *The axle load of the first (steering) axle of – fully loaded – 5 and 6 axle articulated vehicles. International experience has shown that the load on this axle lies normally in a narrow bandwidth between 6,5 and 7,0 tonnes.*
- 4) *The axle distance between the 2<sup>nd</sup> and 3<sup>rd</sup> (driven) axles of 6 axle Tractor + Semi-trailer combinations. International experience has shown that the distance between these axles is very stable at 1,30 m as this allows the highest loads.*

These tests can be used to compare the quality from one WIM site with another one (relative quality) by seeing how much the four test's means and standard deviations differ. One can also calculate the absolute quality if one of the sites has an acceptable and quantified data quality.

What is most interesting for my thesis is to examine the load of the front axles (3) and the distance between the second and third driven axles (4) and see how they correspond to the standard values. The reason for choosing those is that length and gross vehicle weight regulations can change depending on the country. E.g. in Norway, the maximum gross vehicle weight for semi-trailers is 50 tonnes,<sup>20</sup> although drivers are not fined before they surpass 52 tonnes. Some special vehicles are also allowed to deviate from these maximum weights.<sup>21</sup> Further, the maximum length for truck + semi-trailer in Norway is 17,50 m, one meter longer than what is stated in 1). Because of the dissimilar limits, only 3) and 4) will be examined as we assume that these parameters remain relatively constant.

#### Report on WIM-system data analysis

A new report, Maria Elena Palma Tello's *Report on WIM-system data analysis*<sup>22</sup> consists of comparisons between gross vehicle and axle weights and their corresponding static weights. The author wanted to estimate the accuracy of the WIM data by estimating the relative errors, as well as checking for which accuracy class the data satisfy according to the European specification COST 323. This specification gives recommendations for finding potential WIM sites, installation, operation, calibration and assessment of the output from such systems. Further methodology was to have a criteria for data selection, at which vehicles with an absolute error larger than 20 % is not considered. Faulty number plate matching, static weighing errors and lack of static weight measurements was assumed to cause the large errors.

The results from the GVW were an average error of 2,73 % and a standard deviation of 6,77 %, which implies an overestimation of the WIM weights. When the single axles were weighed separately and compared with the WIM weights, the results were more scattered with the averages oscillating between -5,21 % and 8,65 %. The standard deviation was from 10,07 % to 14,31 %. The heaviest vehicles (n = 99) satisfied accuracy class B (10), which means

that 95 % of the errors were within 10 % of the static weight, while all vehicles (n = 511) satisfied class C (15). The conclusion is that the WIM sensor's accuracy is good, and adequate for pre-selection of vehicles for law enforcement.

#### Assessment of classification systems for vehicles

A report by Erlend Aakre, *Vurdering av klassifiseringssystem for kjøretøy*<sup>15</sup> (Assessment of classification systems for vehicles) states that vehicle composition statistics is important to provide input to traffic models and road design. He has also written that certain standards assess the data quality of WIM and tell how the data can be used for miscellaneous road purposes. Some of those standards include COST 323, a European specification for WIM, and ASTM, an American WIM standard that includes user requirements and test methods of such systems.

Furthermore he compares dynamic and static loads from WIM sensors by using linear regressions and corrects the data to obtain weights that are more accurate. The accuracy of the WIM systems turn out to be not so good, with the WIM system Datarec410 giving a deviation of 35 % of the static weight on a 95 % confidence level. The other WIM system used, VIPERWIM, had a deviation of 25 % at the same confidence level. A combination of the two systems resulted in a deviation of 15 %.

By correcting the dynamic WIM weights by using equations from several linear regressions, Aakre obtained an accuracy improvement of the Datarec410, but not for the VIPERWIM system. It became worse. To improve this analysis several length class correction factors were applied and a length classification class for different vehicles were proposed.

### 1.2. Research questions

The aim of this Master's thesis is to examine if there are parameters that can describe the relationship between the dynamic weights from WIM and the static weights. The parameters that are going to be examined are gross vehicle weights (GVW), front axle weights and the weights of 2<sup>nd</sup> and 3<sup>rd</sup> axles combined.

For the GVW, three sets of data are considered. The weights from heavy vehicles with five axles and six axles will be looked at. In addition, an aggregation of all the heavy vehicles will be made and named as "all axles". Furthermore, the front axle weights and the added weight of the 2<sup>nd</sup> and 3<sup>rd</sup> axles will be from six axle vehicles. The final group is chosen as a parameter because I think that the weight will remain somewhat constant. In total there will therefore be five groups of different axle combinations.

In addition, I will study if the relationships between the WIM and static weights remain stable over time, as it has been experienced that the WIM systems' accuracy often worsen after some time. This means that an increasing difference between the WIM and static weights can

occur. I will also examine if the obtained results from one arbitrary site can be applied to different WIM sites, in order to see if the findings are general or just apply locally.

Next, I will look at certain parameters from the WIM data to try and assess the data quality, as suggested in Loo and Lees' report *Standard quality checks for weigh-in-motion data*. The parameters examined are the average front axle load of vehicles with five and six axles, as well as the average distance between the 2<sup>nd</sup> and 3<sup>rd</sup> axles. We want to see if their values change at different WIM sites. Like Loo and Lees' report, the mean front axle load should be between 6,5 and 7,0 tonnes, while the mean axle distance should be 1,30 meters.

At the end of this thesis, I will calculate calibration coefficients, which can be used to adjust the dynamic weights. Hopefully the WIM weights will be close to their corresponding static weights, thus making this a good method for acquiring better vehicle composition statistics.

Similar examinations for lighter vehicles (< 3,5 t.) will not be performed due to time constraints.

### 1.3.Hypothesis

The following hypotheses are going to be examined in this Master's thesis:

#### **H1:**

- a<sub>1</sub>: There is a difference between the WIM weights and the static weights.
- a<sub>0</sub>: The WIM weights and the static weights are the same.

#### **H2:**

- b<sub>1</sub>: There is a time-dependent difference between the WIM weights and the static weights.
- b<sub>0</sub>: The WIM weights and the static weights do not change over time.

#### **H3:**

- c<sub>1</sub>: The difference between the WIM weights and the static weights is not the same at different WIM sites
- c<sub>0</sub>: The difference between the WIM weights and the static weights is the same at different WIM sites.





## 2. Weigh-in-motion (WIM)

### 2.1. History

WIM systems were first introduced in the US in the 1950s and have since then been developed further, with additions of various sensors and techniques. A representative WIM site, seen in figure 3, comprises some sensors (bending plates, quartz sensors or piezoelectric cables) which measure the axle weights, an inductive loop for detecting a passing vehicle's presence, a roadside cabinet for processing the incoming signals from the sensors and a system that transmits data to the responsible authority.<sup>23</sup> The inductive loop will sense the presence of metallic objects (vehicles), "by detecting the perturbation (known as a magnetic anomaly) in the Earth's magnetic field created by the object."<sup>24</sup> Figure 1 shows how the magnetic field is perturbed by a ferrous material.

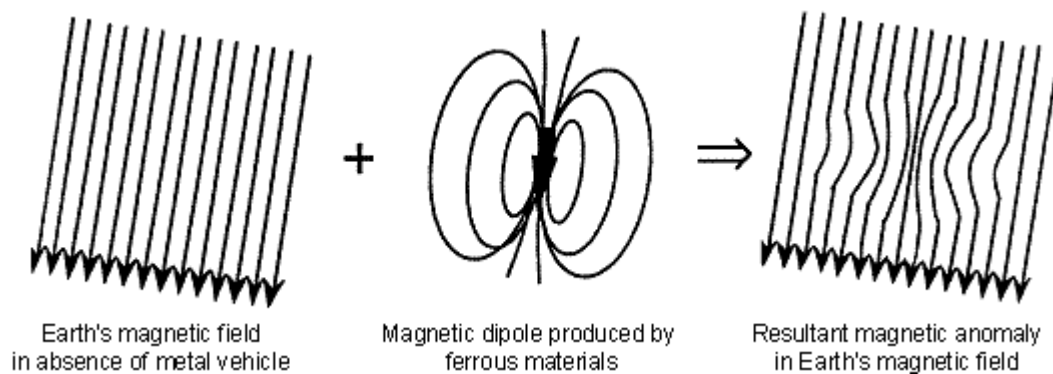


Figure 1: Earth's magnetic field disturbed by a ferrous material (vehicle). Figure: FHWA<sup>25</sup>.

Several types of sensors are used for WIM and are as follows:

- Bending plates.
- Strip sensors (piezo-ceramic, piezo-polymer, piezo-quartz, fibre-optic and gauge strip load cell).

Below, a few of those will be described.

The first sensors reaching the market were bending plates (scales)/load cells, fixed in frames that are installed in the road superstructure, see figure 2. Strain gauges are fixed to the underside of the plate and when load is applied, the strain is subsequently measured. By using the acquired dynamic load from a moving vehicle and some calibration factors, the static load can be estimated.<sup>26</sup> This kind of weigh-in-motion system is used as a low-speed WIM (LS-WIM), where the operating speeds are in the range of 5 to 15 km/h.<sup>14</sup>

There are however several disadvantages with this system. Firstly, it requires a considerable amount of engineering work to install the plates into the asphalt layer, and secondly, modifying the pavement for the installation can result in grooves, holes and make the plate come loose, all of which can cause a significant danger.<sup>26</sup>



*Figure 2: WIM bending plates scale. Figure: IRD.<sup>27</sup>*

The second type of sensors hitting the market were strip sensors, introduced in the beginning of the 80s. They consist of either round or flat cables that span the traffic lane they measure, laid down in a 3/8" (9,5 mm) deep groove<sup>28</sup> which is cut transversally to the lane direction. Systems with strip sensors are used as high-speed WIM (HS-WIM) and operate at normal road velocities.<sup>14</sup>

One type of strip sensors is fiber optic cables. Fiber optical cables consist of a mantle with higher refractive index, which is defined as the speed of light in vacuum divided on the speed of light in the given medium,<sup>29</sup> surrounded by a coating with lower refractive index.<sup>30</sup> Thus, when light is introduced at shallow angles of incidence, total internal reflection at the interface between the materials will ensure that an almost lossless transmission of light is possible.<sup>31</sup> Mechanical disturbances like loads on the cable will result in changes in the angle of incidence that the light beam encounters throughout its path. This can be exploited to construct sensors where the light leaks out of the cable proportional to the load, and then the weight of the load may be estimated from the intensity of the transmitted light.<sup>32</sup>

A more modern type of load cells is gauge strip sensors that consist of a 3" wide load cell, in which strain gauges are mounted. The system is capable of measuring speeds up to 130 km/h<sup>33</sup> and can therefore be regarded as a HS-WIM, in contrast to the old load cell system (LS-WIM).

Another type of strip sensors is piezoelectric sensors. Crystals and ceramics that get an electric charge when they are compressed, distorted or twisted are said to be piezoelectric.<sup>34,35</sup> The mineral quartz in crystal form has good piezoelectric properties, is extremely stable and is therefore often used as piezoelectric strip sensors in WIM systems. Kistler, a producer of measuring systems and sensors, uses quartz crystal sensors in their Lineas<sup>®</sup> WIM sensor technology. It has an aluminium alloy profile in which quartz discs are fitted, allowing only

measurements of vertical forces and no lateral forces.<sup>36</sup> This system is claimed to be highly accurate.<sup>37</sup> Figure 4 shows a piezoelectric cable in the asphalt.

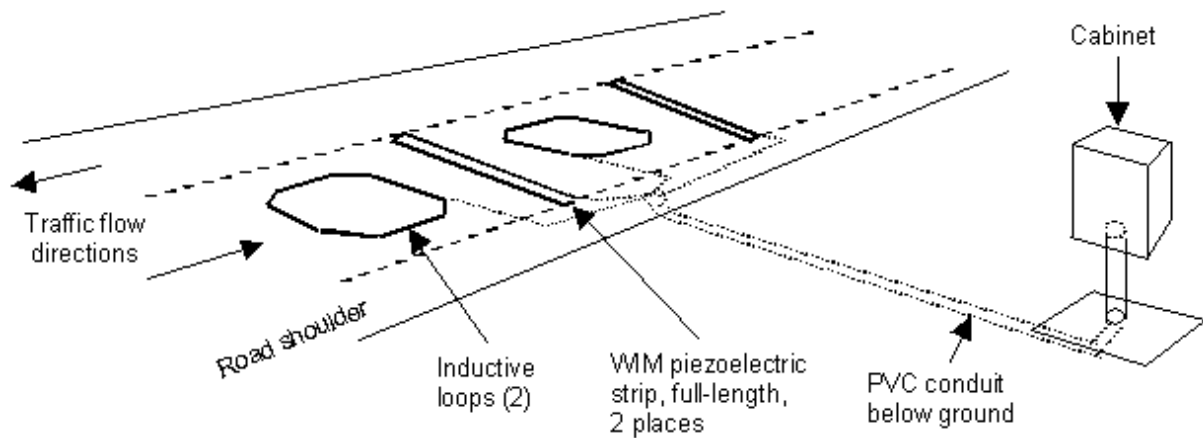


Figure 3: A typical WIM setup of piezoelectric strip sensors. Two inductive loops can be seen alongside with two piezoelectric strips. Figure: FHWA<sup>38</sup>.

An advantage of a piezoelectric system is its relatively low installation costs compared to the instrumented plates discussed in the paragraph a few sections above. The required engineering work is far less and cutting a few centimeters groove in the asphalt surface is a quick task. Despite this seemingly clear advantage, this kind of WIM system does not measure loads directly, since the tire imprint is surpassing the width of the cable. However, HS-WIM has some limitations regarding the accuracy of the measurements that is caused by the dynamic interaction between the road and the wheels. Thus, the accuracy of such systems can vary from 10 to 25 % for approximately 95 % of the gross vehicle weights.<sup>39</sup> The cables also have to be replaced once every three years.<sup>40</sup>

More modern WIM systems, like multiple-sensor WIM (MS-WIM), consist of placing several road sensors, e.g. piezoelectric ones, at a uniform or non-uniform spacing on a road section. By averaging the measured loads from each sensor, the accuracy can be improved.<sup>41</sup> The accuracy of such systems is depending on the pavement profile, the number and quality of the sensors and the algorithm and data processing. MS-WIM has an accuracy of 7 to 10 % for approximately 95 % of the gross vehicle weights.<sup>39</sup>

Another type of WIM is bridge WIM (B-WIM) that uses a bridge as a large scale, which is calibrated to weigh vehicles. Instrumented bridge parts, like a deck or slab, is utilised to measure the strain (bridge deformation) that occurs when a moving vehicle is crossing the bridge,<sup>42</sup> see figure 5. Thus, by using algorithms with the output from the strain sensors, the axle and vehicle loads can subsequently be calculated.

Many B-WIM systems also require an axle detector to count the axles, measure axle distances and axle speeds in order to work properly.<sup>43</sup> However, some developed algorithms remove the need for such detectors. One is the free of axle detector algorithm (FAD), developed at the Laboratoire Central des Ponts et Chaussées, which is recommended for short frame type bridges and some other types.<sup>44</sup>



Figure 4: Strip sensors (piezoelectric) mounted in the asphalt. Photo: Torbjørn Haugen

Under average circumstances, B-WIM from Cestel is claimed to have an accuracy of 10 to 15 % for 95 % of the measurements.<sup>45</sup>

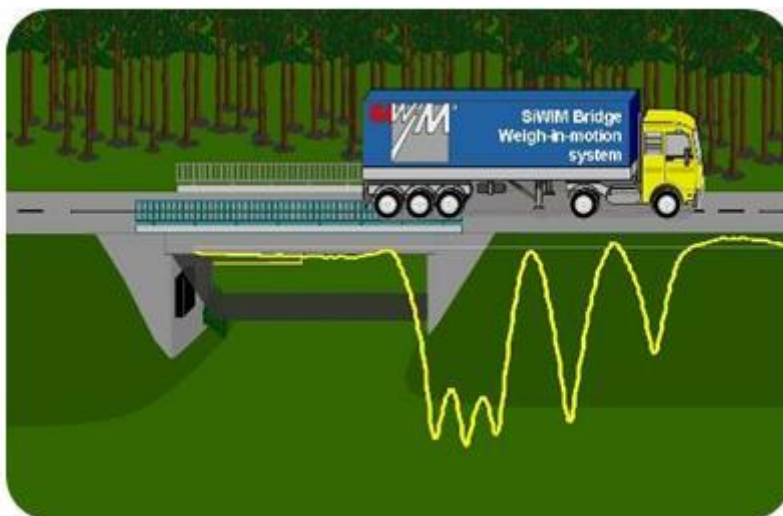


Figure 5: Strains induced on at B-WIM by a moving vehicle. Source: UAB School of Engineering.<sup>46</sup>

## 2.2.Applications of WIM systems in Norway

Traffic enforcement cameras (TEC, in Norwegian: ATK) are normally used to enforce speed limit violations. In Norway, pressure sensors, like piezoelectric cables, are used to control this. This is highly unusual in an international context, as radars and lasers mostly are used for traffic enforcement.

Internationally, weigh-in-motion sites are entirely dedicated to weight enforcement. They comprise temperature sensors and road site processing units, made specifically for interpretation of the sensor signals. In addition, systems for signal calibration are used. This equipment is not used in Norway and we thus have a form of simplified WIM.<sup>47</sup>

There are two types of TECs that are used in Norway. One is a single-TEC, figure 6, where the speed is controlled at one site, and the other one is section control TEC where it is measured over a longer distance.<sup>48</sup> At the first type, the speed is found by calculating the time used for passing one pressure sensor to another with a uniform spacing. If the speed is too high, a picture of the vehicle is taken by the TEC and the driver is subsequently fined.

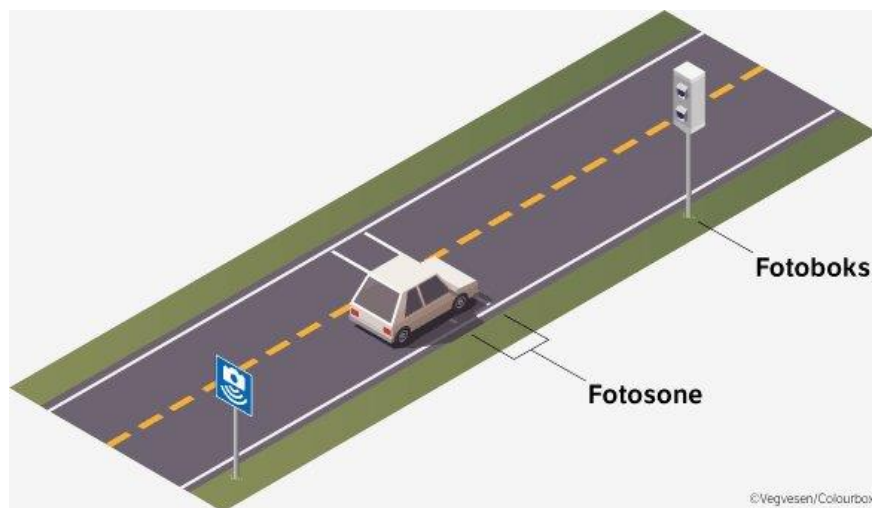


Figure 6: Single-TEC. A traffic enforcement camera (fotoboks) is placed next to the road. The two transversal lines delimit the photo zone (fotosone) in which a picture is taken in case of speeding. The pressure cables cannot be seen here. Photo: Vegvesen/Colourbox<sup>49</sup>.

The section control consists of two TECs; one at the beginning and one at the end of a road section. At both places, the number plates and times are captured, enabling the calculation of the average speed. In case of speeding, a picture of the vehicle is taken and sent to the police for enforcement.

In this thesis, weight data from both single-TEC and section control TEC will be used.

### 2.3. WIM system accuracy

The accuracy of different WIM systems can vary a lot depending on the road conditions. For each axle that passes the sensor, WIM measures the instantaneous dynamic force. Due to the interaction between the tire and the sensor, this dynamic force can vary significantly from the static axle load. The following parameters influence this interaction:

- Tire pressure
- Vehicle dynamics (speed, vibrations, suspension, load balance, acceleration, deceleration etc.)
- Road surface roughness
- Sensor conditions
- Weather conditions

Because of this, single-sensor WIM systems can have an accuracy that ranges from 15 % to 30 %. Improved systems with multiple sensors, MS-WIM, have an accuracy from 5 % to 8 %.<sup>50</sup> Varying accuracy is however not an unknown problem. COST 323 Final Report also writes about what is influencing this interaction (my parenthesis in the quote below):

«In addition to the force of gravity, this force (dynamic vehicle tyre force) can include the dynamic effects of influences such as road surface roughness, vehicle acceleration, out-of-round tyres, dynamically unbalanced wheels or tyres, tyre inflation pressure, vehicle suspension and aerodynamic features and wind.»<sup>51</sup>

The Office of Highway Policy Information says that even when the WIM sites are properly installed, structural anomalies and unexpected deterioration occur. An example is that softening asphalt pavement in hot weather will worsen the measurement. In general, they say that the accuracy of WIM systems depends on four main factors:<sup>52</sup>

- Vehicle dynamics
- Pavement integrity, composition and design
- Variance inherent in the WIM system
- Calibration

Bjørn Brændshøi at Norwegian Public Roads Administration has said that the road surface integrity, composition and design has a lot to say for the accuracy of the Norwegian WIM systems. Other factors like weather conditions, road wear, temperature and WIM cable depth also affect the accuracy. It can therefore be difficult to point out single reasons why the data from WIM sites sometimes are inaccurate.<sup>53</sup>

Jiang et al. (2009) write in their report *Improvement in Piezoelectric Sensors and WIM Data Collection Technology*<sup>36</sup> about how the pavement temperature influences the piezoelectric sensors' performance. By testing how much the output signals change when the temperature is changing, they found out that Kistler's piezoelectric quartz sensors, used in some of our WIM sites, had stable outputs, though with some inaccuracy. The least error between the WIM weight and the static weight was found at around 30 °C, the temperature to which the

system was calibrated. These findings are important to our task as this might affect our results.

Also, the accuracy can change after some time. The WAVE general report says that pavement wear and ageing, as well as possible changes in traffic conditions can cause this. Furthermore, possible changes in the sensor and system themselves are also thought to influence the accuracy over time. Because of this, periodic calibrations of the systems must be performed. Calibration means to adjust the system outputs so that it gives accurate measurements, as different WIM sites have different local traffic conditions.<sup>54</sup> However, calibration is not performed regularly in Norway as weight data is not the primary goal of WIM.<sup>47</sup>

## 2.4. Classification of WIM systems

Classification of WIM systems improves understanding of the applicability of setups with a given measurement accuracy. Examples are speed limit enforcement, weight limits, acquiring statistics of vehicle composition and designing new roads. Following is a description of two different standards about weigh-in-motion.

The ASTM specification is mainly used for model approval or to find upper limits of performance that can be achieved by different types of WIM systems. The main objective of COST 323 is however to provide a complete specification that covers both model approval and using European standards to perform site acceptance tests and accuracy assessments. Therefore, only COST 323 will be used in this thesis.<sup>55</sup>

### 2.3.1. ASTM E1318 - 02

ASTM International, one of the largest standards developing organisations in the world,<sup>56</sup> has developed a standard for classification of WIM systems. It is called Standard Specification for Highway Weigh-In-Motion (WIM) Systems with User Requirements and Test Methods and is designated by E 1318 – 02. The standard proposes four different WIM types used for different road purposes, with corresponding accuracy tolerance limits, seen in table 1.

**Type I:** Shall be able to register highway vehicles moving at speeds from 16 to 130 km/h,<sup>57</sup> as well as being capable of producing continuous high-quality data for the registered vehicles. Some of the data might be:<sup>58</sup>

- Time and date
- Lane
- Speed
- Vehicle Classification
- Wheel load
- Axle Load

- Individual Axle Spacings
- Gross Vehicle Weight
- Overall Vehicle Length

**Type II:** Shall be able to register highway vehicles moving at speeds from 24 to 130 km/h. All features of this type shall be the same as in type I.<sup>59</sup> This is equipment with lower costs and can typically have piezoelectric cables.<sup>60</sup>

**Type III:** Used to identify vehicles suspected of load-limit violation and works at the same speed range as Type I.<sup>60</sup>

**Type IV:** Used to identify vehicles suspected of load-limit violation at low speeds (3 to 16 km/h).

The ASTM further states some functional performance requirements for WIM systems. These should be satisfied and are as following:

*Table 1: ASTM types of different functions and their corresponding tolerance limits.*

Function	Tolerance for 95 % Probability of Conformity				
	Type I	Type II	Type III	Type IV	
				Value ≥ lb (kg)	± lb (kg)
Wheel Load	± 25 %		± 20 %	5000 (2300)	300 (100)
Axle Load	± 20 %	± 30 %	± 15 %	12 000 (5400)	500 (200)
Axle-Group Load	± 15 %	± 20 %	± 10 %	25 000 (11 300)	1200 (500)
Gross-Vehicle Weight	± 10 %	± 15 %	± 6 %	60 000 (27 200)	2500 (1100)
Speed	± 1 mph (2 km/h)				
Axle-Spacing	± 0.5 ft (0.15 m)				

### 2.3.2. COST 323 classification

COST 323 is a European specification for WIM that gives recommendations for potential sites, installation, operation, calibration and assessment of the output from WIM systems. It also includes some user and performance requirements to assess the accuracy of WIM systems, found in table 2. COST is short for “Co-Operation for Science and Technology” and the objectives are to provide a common technical background for experts and facilitate co-operation.

The accuracy of WIM systems is defined by an accuracy class, which is denoted by a letter with a weight tolerance in percent that is the confidence interval width. E.g. A (5) means that



at least a specified proportion or percentage  $\pi_0$  of the dynamic GVWs will be within  $\pm 5\%$  of the static GVW. Whereas  $\pi_0$  depends on the test conditions, seen in table 3, the confidence interval width depends on the axle combination (GVW, single axle, a group of axles, etc.) and the accuracy class<sup>61</sup>.

Seven accuracy classes are proposed, each of them with a corresponding range of requirements and applications. The classes are as following<sup>62</sup>:

**Class A (5):** Used for enforcement of legal weight limits.

**Class B+ (7):** Used if Class A requirements are not satisfied; used for preselection of overloaded vehicles.

**Class B (10):** Can be used to give accurate information for infrastructure design and preselection of overloaded axles or vehicles.

**Class C (15) or D+ (20):** Used for detailed statistical studies, load histograms and infrastructure studies.

**Class D (25):** Can be used for economical and technical studies, and for wide weight classes (5 t.)

**Class E (> 25):** Used for acquiring traffic composition, load distribution and frequency at systems installed on poor quality WIM sites.

*Table 2: COST 323 accuracy classes and their corresponding confidence intervals widths for different criteria.*

Criteria (type of measurement)	Domain of use	Accuracy Classes: Confidence interval width $\delta$ (%)						
		A (5)	B+ (7)	B (10)	C (15)	D+ (20)	D (25)	E
1. Gross weight	Gross weight > 3.5 t	5	7	10	15	20	25	> 25
Axle load:	Axle load > 1 t							
2. group of axles		7	10	13	18	23	28	> 28
3. single axle		8	11	15	20	25	30	> 30
4. axle of a group		10	14	20	25	30	35	> 35
Speed	$v > 30$ km/h	2	3	4	6	7	10	10
Inter-axle distance		2	3	4	6	8	10	10
Total flow		1	1	1	3	4	5	> 5

In table 2, we can see that the confidence intervals widths depend on which type of measurement that is used. E.g. we can see that gross weight has stricter limits than single axles. This means that the more axles that are examined at once, the lower are the

confidence interval widths. The reason for this is that mean random error from several axles will be lower than the random error from one axle.

From this and the previous table (table 1) we can see that ASTM Type I for GVW ( $\pm 10\%$ ) equals COST 323 accuracy class B (10). Another example is ASTM Type II for GVW ( $\pm 15\%$ ) equals COST 323 accuracy class C(15). This means that the tables have relations to each other. Our relevant criteria from Table 2 will be 1. *Gross weight* for GVW, 2. *Group of axles* for the 2<sup>nd</sup> and 3<sup>rd</sup> axles load and 3. *Single axle* for the front axle load.

## 2.4. Procedures to check the accuracy and repeatability

There are several ways to assess the accuracy of a WIM. Since the tests may be performed during various periods, we need to classify our tests with regards to their environmental repeatability or reproducibility.<sup>63</sup> By repeatability it is meant “closeness of the agreement between the results of successive measurements of the same variable carried out under the same conditions” and by reproducibility “closeness of agreement between the results of measurements of the same variable carried out by similar instruments under different conditions”.<sup>64</sup>

- (I) **Environmental repeatability:** Limited test period (a couple of hours) during one day or over several consecutive days, thus ensuring stability in temperature, climatic and environmental conditions.
- (II) **Limited environmental reproducibility:** Time period extending over at least one week or several days over a month. Temperature, climatic and environmental conditions may vary, but with no seasonal effect considered.
- (III) **Full environmental reproducibility:** Time period extending over a whole year or several days over a year, thus probing the effect of seasonal variations in temperature, climate and environment.

Furthermore, we need to examine the repeatability and reproducibility conditions of the vehicles passing our test sites. The conditions include one vehicle passing one site multiple times or many vehicles passing just one site. They are as follows<sup>65</sup>:

- (r1) **Full repeatability conditions:** One vehicle passing several times at same speed, with same loads and same lateral position
- (r2) **Extended repeatability conditions:** One vehicle passing several times at different speeds and loads, but with small lateral displacement variations.
- (R1) **Limited reproducibility conditions:** 2 - 10 vehicles, representative of the whole traffic composition, passing at different speeds and loads.
- (R2) **Full reproducibility conditions:** A large sample of vehicles (10 – over 100s), same conditions as R1.

Our measurements satisfy (I) as we will only collected data during a few hours during one day, and (R1) or (R2) since our sample sizes can range from about 5 and more.

Table 3: Minimum levels of confidence  $\pi_0$ , of the centred confidence intervals (in %) – case of a test under «(I) environmental repeatability»<sup>66</sup>.

Test conditions\ Sample size (n)	10	20	30	60	120	$\infty$
Full repeatability (r1)	95	97,2	97,9	98,4	98,7	99,2
Extended repeatability (r2)	90	94,1	95,3	96,4	97,1	98,2
Limited reproducibility (R1)	85	90,8	92,5	94,2	95,2	97
Full reproducibility (R2)	80	87,4	89,6	91,8	93,1	95,4

In table 3, we can see the minimum levels of confidence needed. By looking at  $\pi_0$  as the sample size increases, we can see that the confidence level also increases. However, obtaining large sample sizes takes time and a high level of confidence can thus not always be achieved.

## 2.5.How to find suitable sites for WIM installations

In order to acquire high-quality data from WIM systems, a potential WIM site needs to fulfill several criteria that concern pavement characteristics and road geometry. If they are not fulfilled, large discrepancy may occur because of the in-motion vehicle behavior.

COST 323 has a whole chapter about WIM systems in which several requirements for the WIM sites have been proposed. The requirements for the road geometry are to have some length before (50 m) and after the WIM site (25 m) with a given longitudinal and transverse slope and a minimum radius of curvature. The WIM site should also be installed away from places with deceleration and acceleration, to assure a uniform weight distribution and avoid weight shifting due to speed changes.

The geometric requirements are as follows:

- Longitudinal slope < 1 % (class I site, see table 4 below) or < 2 % (other site classes), depending on the site class.
- Transverse slope < 3 %
- Radius of curvature > 1000 m, although a straight road section is preferred

It is however not always possible to achieve the geometric requirements in real life due to the fact that the road is already build and can oftenly not be changed. As a consequence, this might generate errors, which cannot be fixed just by adjusting the WIM system itself.

Furthermore, the pavement characteristics for site criteria listed in table 4 below consist of rutting, deflection and evenness limits. The preferred condition is low levels of deflection, rutting and roughness to improve sensor performance.<sup>67</sup> It is important to consider those factors when WIM sites are assessed. This is because a poor WIM site, i.e. a site with

unfulfilling criteria, will perform worse than a good site. Nevertheless, replacing poor quality asphalt is easier than changing the road's geometry.

Table 4: COST 323 WIM site classes and their criteria's limits. IRI = international roughness index, APL = device that measures longitudinal profile of

			WIM site classes		
			I Excellent	II Good	III Acceptable
<b>Rutting</b> (3 m – beam)		Rut depth max. (mm)	≤ 4	≤ 7	≤ 10
<b>Deflection</b> (quasi-static)  (13 t – axle)	Semi-rigid pavements	Mean deflection (10 <sup>-2</sup> mm)	≤ 15	≤ 20	≤ 30
		Left/Right difference (10 <sup>-2</sup> mm)	± 3	± 5	± 10
	All bitumen pavements	Mean deflection (10 <sup>-2</sup> mm)	≤ 20	≤ 35	≤ 50
		Left/Right difference (10 <sup>-2</sup> mm)	± 4	± 8	± 12
	Flexible pavements	Mean deflection (10 <sup>-2</sup> mm)	≤ 30	≤ 50	≤ 75
		Left/Right difference (10 <sup>-2</sup> mm)	± 7	± 10	± 15
<b>Deflection</b> (dynamic)  (5 t – load)	Semi-rigid pavements	Deflection (10 <sup>-2</sup> mm)	≤ 10	≤ 15	≤ 20
		Left/Right difference (10 <sup>-2</sup> mm)	± 2	± 4	± 7
	All bitumen pavements	Deflection (10 <sup>-2</sup> mm)	≤ 15	≤ 25	≤ 25
		Left/Right difference (10 <sup>-2</sup> mm)	± 3	± 6	± 9
	Flexible pavements	Deflection (10 <sup>-2</sup> mm)	≤ 20	≤ 35	≤ 55
		Left/Right difference (10 <sup>-2</sup> mm)	± 5	± 7	± 10
<b>Evenness</b>	IRI index	Index (m/km)	0 – 1.3	1.3 – 2.6	2.6 - 4
	APL	Rating (SW, MW, LW)	9 – 10	7 – 8	5 - 6

## 2.6. Our WIM sites

During this Master's thesis, we have collected data from several WIM sites in Norway. Our sites were chosen because of their availability and not because they necessarily satisfy the WIM site criteria mentioned in the previous paragraph. We will only do a rough assessment by eyesight of the site characteristics, but not calculate which class the sites are.

In total, we examine five different WIM sites, and of those, one site (WIM 1740104) will be examined twice. Thus, we will have six different data sets from three dates to work with:

- WIM 1740009 - 11/11-2015.
- WIM 1740104
  - o 1740104(1) - 11/11-2015.
  - o 1740104(2) - 18/3-2016.
- WIM 540032 - 27/4-2016.
- WIM 540031 - 27/4-2016.
- WIM 540109 - 27/4-2016.

In figure 7, WIM 1740104 and WIM 1740009 can be seen on a map. The traffic station is seen in the upper right corner.



Figure 7: Map of the WIM sites 1740104 and 1740009 and the traffic station on road E6 Åsen.



*Figure 8: Picture of WIM 1740009. The two transversally laid WIM cables can be seen in the front of the picture. Photo: Torbjørn Haugen.*

**WIM 1740009**, figure 8, the site furthestmost to the east, with approximate coordinates (63.590732, 11.022882), has according to Google Maps' measuring tool a straight road section with some undetermined longitudinal slope. The inclination was considerable, so it is not sure if the limits of  $< 1\%$  and  $< 2\%$  can be satisfied. It can also be seen that there are some wheel ruts in which water is running. Consequently, this has the possibility to have an impact on the accuracy of the data. This site utilises round piezoelectric cables. Data from this site was acquired on 11/11-2015.

**WIM 1740104**, figure 9, the other WIM site with approximate coordinates (63.542803, 10.863441), has a long enough straight road section to satisfy the requirements stated in the section above. The inclination here is undetermined, but it seemed rather low. No wheel ruts were clearly visible during the inspection. This site utilises round piezoelectric cables.

This site is used twice in this thesis. For that reason, a distinction between the two times has to be made. 1740104(1) will denote the first data set from the 11/11-2015 and 1740104(2) will denote the second data set from 18/3-2016.



Figure 9: Picture of WIM 1740104. The location of the cables can clearly be seen. Photo: Torbjørn Haugen.

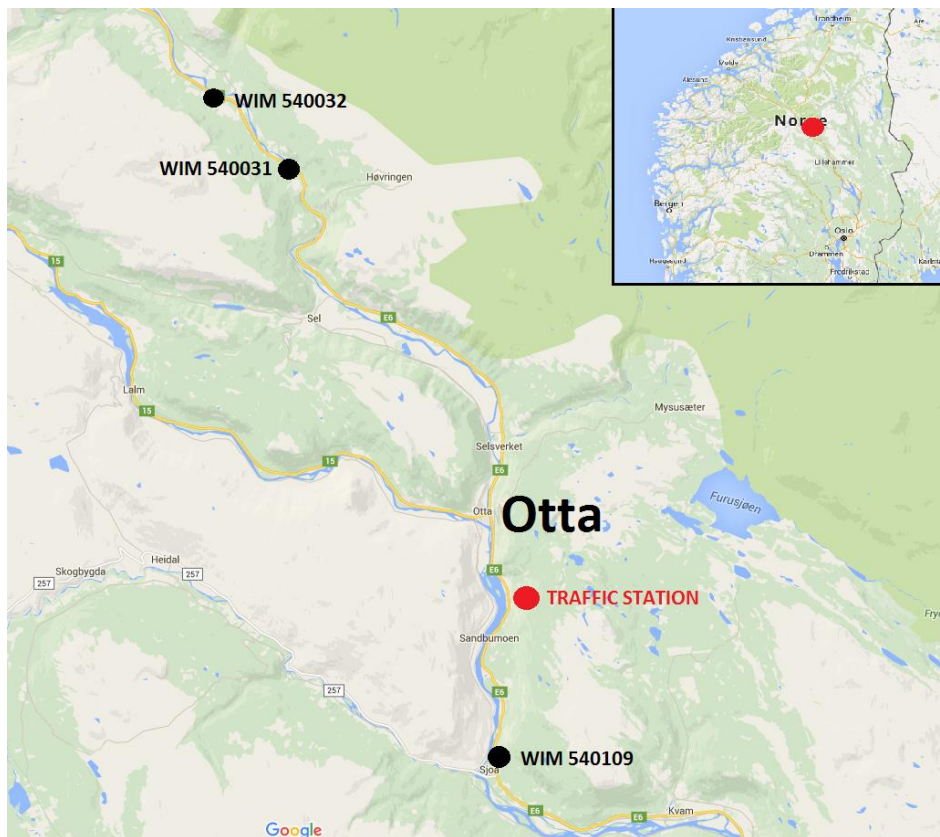


Figure 10: Map of the WIM sites 540032, 540031, 540109 and the traffic station at Otta.

In figure 10, sites WIM 540032, WIM 540031 and WIM 540109 can be seen on a map, along with the traffic station. The two first sites are a section control TEC, while WIM 540109 is a normal TEC.

**WIM 540032**, seen in figure 11, the northmost WIM site of a section control TEC (connected to WIM 540031) with approximate coordinates (61.920236, 9.341202). This site is situated on road E6 close to Brennhaug, Dovre in Norway. This site had a low longitudinal inclination and a long enough road section before and after it. This WIM site seems to satisfy the class criteria quite well. This site utilises flat piezoelectric cables. Data from this site was acquired on 27/4-2016.

**WIM 540031**, seen in figure 12, the southmost site of the section WIM (connected to WIM 540032) with approximate coordinates (61.89562, 9.395043). At this point, there was a small pothole, though not dangerous for vehicles, in the road just before the WIM cables that could shift the load distribution. Otherwise, the site had a long and flat straight road section before and after the measurement point, though with some visible wheel rutting. The criteria are probably not satisfied at this site. This site utilises flat piezoelectric cables. Data from this site was acquired on 27/4-2016.



*Figure 11: Picture of WIM 540032. The piezoelectric cables of the northbound WIM site can be seen.  
Photo: Torbjørn Haugen.*





*Figure 12: Picture of WIM 540031. Cables at the southbound WIM site. The thick black lines are due to some surface filling. The pothole cannot be seen in this picture. Photo: Torbjørn Haugen.*

**WIM 540109**, figure 13, the WIM site close to Sjoa, Norway with approximate coordinates (61.669554, 9.567545). This site is situated south of Sjoa, Norway. The asphalt pavement had some visible signs of wheel rut, but otherwise the site was situated in a downhill and straight road section. Consequently, the quality of this site is uncertain with respect to the criteria stated in the previous chapter. This site utilises round piezoelectric cables. Data from this site was acquired on 27/4-2016.



*Figure 13: Picture of WIM 540109. Two cables and one processing unit box, the big box in the middle of the picture, can be seen. Photo: Torbjørn Haugen.*

### 3. Methodology

In research, it is normal to use both qualitative and quantitative methods to search for answers to the issues or hypotheses that are being investigated. With the use of qualitative methods, understanding and analysis of interrelations are being emphasized,<sup>68</sup> which can be observations of behaviour, data from interviews and questionnaires. Quantitative methods use numbers and static units that can be quantified,<sup>69</sup> such as registration of data that can be followed by statistical analysis.<sup>70</sup> Qualitative methods can furthermore generate new hypotheses that can be investigated quantitatively, as well as elaborating quantitative results and they are therefore complementary methods, which cannot substitute each other.<sup>69</sup>

In this Master's thesis quantitative methods will mostly be used. The reason for this is that I work with a quantitative standard, thus such methods must be used. The registration and processing of data will go as follows:

- 1) Collect data from WIM sites and compare with static weights for a short period. This can be from one single day.
- 2) Analyse data from one WIM site over time to see if and how much the accuracy changes.
- 3) Collect data from other WIM sites to see if the interrelationships are transferable to other WIM sites.

In the following paragraphs, the numbers above will be elaborated more thoroughly. To assess the general data quality, each WIM site will be evaluated according to Loo & Lees' (2015) scientific paper *Standard quality checks for weigh-in-motion data*.

#### 3.1. Method for weighing vehicles

The weighing is being done by intercepting heavy vehicles (>3,5 tonnes) from the traffic stream into the traffic station with the use of electronic signs. After that, they are weighed on a static weight, figure 15, which is used as the reference weight as the error is small and known ( $\pm 20$  kg). Since the static scale weight is five meters long and heavy vehicles usually are longer than that, all the axles of a vehicle cannot fit onto the scale at once. Thus, only a few of the axles can be weighed each time. For a lorry with five axles, a possible weighing order can be to first weigh the front and second axle, and then the three last ones, which can be represented by the numbers (1+2, 3+4+5). In table 5, an example from a five axle vehicle is shown. The table has five columns for axles, as the weighing order changes depending on each vehicle's (with five axles) characteristics.

Table 5: Static axle weights of a vehicle with five axles that can be represented by (1, 2+3, 4+5). Axle 1 is 6,42 tonnes, axle 2 and 3 are 9,1 tonnes etc. Summing them gives a total weight of 25,18 tonnes.

1	2	3	4	5	Total
6.42		9.1		9.66	25.18

This means that what we measure is the added axle weights of each «combination» of axles. Summing them all up will consequently give the gross vehicle weight. In figure 14, we can see the weight output on a screen at the traffic station. Table 6 is showing different combinations we registered during our first data acquisition in November 2015:

Table 6: Different number of axles with their possible axles combinations. The numbers 1 to 6 in the static weight columns refer to the axles measured, i.e. 1 is axle 1, 2 is axle 2 etc. Static weight – 1 means first weighing, static weight – 2 means second weighing etc.

Number of axles	Static weight - 1	Static weight - 2	Static weight - 3	Static weight - 4
2	1	2		
3	1	2+3		
	1	2	3	
4	1+2	3+4		
	1	2	3+4	
	1	2	3	4
	1	2+3	4	
5	1	2+3	4+5	
	1	2+3	4	5
	1	2	3+4+5	
6	1	2+3	4+5+6	
	1	2+3+4	5+6	
	1	2+3	4	5+6
	1	2+3	4+5	6
7	1	2+3	4+5	6+7
	1+2	3+4	5+6+7	

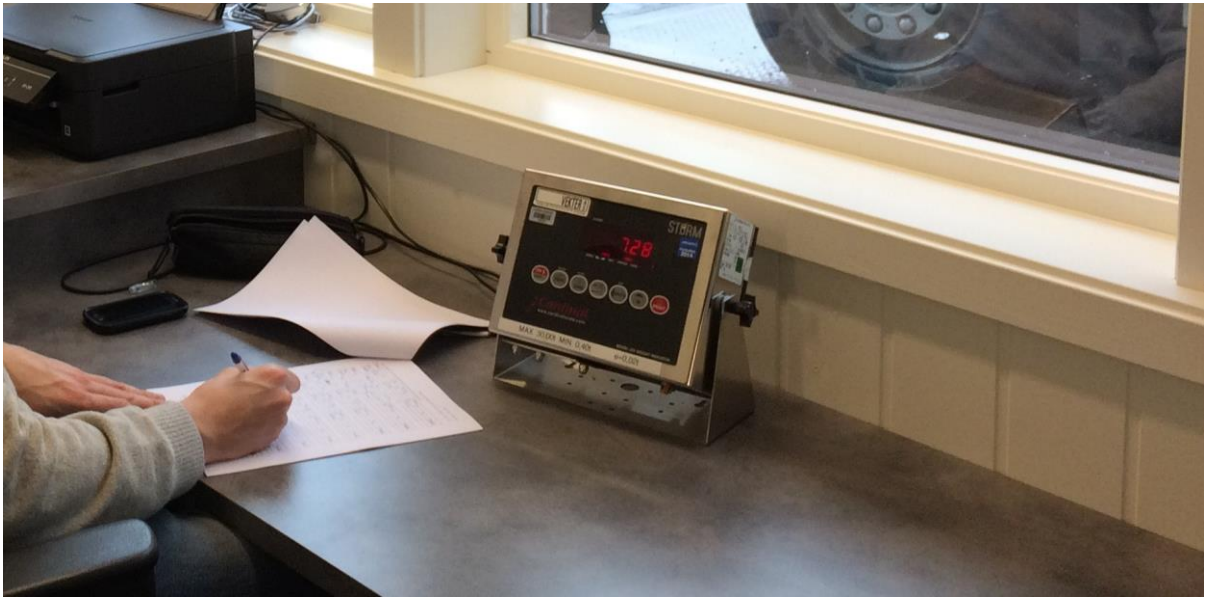


Figure 14: The screen of the weighing device with a registered weight of 7,28 tonnes. Photo: Torbjørn Haugen.



Figure 15: A photo showing the static plate weight at the traffic station, measuring the front axle of a vehicle. Photo: Torbjørn Haugen.

Weigh-in-motion systems identify vehicles at different sites by using automatic number plate recognition. This is performed by traffic enforcement cameras at every WIM site, in case an identification of a vehicle is needed due to a speeding. At section control TECs, the number plates and times at both sites are captured and aggregated into one combined measurement. The aggregated time stamp will denote the time at which the last WIM of the section control was passed.

However, the WIM systems do not save any number plate identifications due to legal reasons. This means we need a method to match vehicles that we have weighed with those registered by the WIM. To succeed with this we have used private video cameras to film vehicles at the WIM sites, so that we can compare those vehicles with those registered at the traffic station. We also know the time at which we started filming with our cameras, thus we can find out when a vehicle passed a site and use the time to find the corresponding vehicle in the WIM data set.

To make this work in practice, we look for some vehicles passing the WIM sites in the videos, and by looking at the vehicle characteristics that we wrote down at the traffic station, we can see if they have been weighed there. If they have, we can try to identify the vehicles in the data set. We use the passing times from the video to help us find the vehicle, as well as looking for a vehicle with the same amount of axles.

To find the rest of the vehicles, we calculate the time gaps between vehicles in the videos and add this to the last vehicle found in the data set. As an example, let us say one vehicle is recognised in the data set and its timestamp is **2016-03-18T13:26:03.301+01:00** (format: yyyy-mm-dd T hh:mm:ss:ms + 01:00/02:00). 01:00 denotes Norwegian winter time and 02:00 summer time. By measuring the time gap between that vehicle to the next one in the video, let that be about 6 seconds, the correct measurement can be found by adding those 6 seconds and the time stamp should subsequently be **2016-03-18T13:26:09.092+01:00**. In table 7, we can see a screenshot from how the data set is presented.

*Table 7: Arbitrary screenshot from the WIM data set on 18/3-2016. Column 1 states the dates and times, while the remaining columns show each axle's corresponding weights in tonnes. The second row shows a vehicle with two axles and axle weights of 0,5 + 0,5 tonnes. Row 6 belongs to a vehicle with six axles.*

Date/time	1740104 1.	1740104 2.	1740104 3.	1740104 4.	1740104 5.	1740104 6.
2016-03-18T04:02:22.854	0,5	0,5				
2016-03-18T04:02:51.534	0,7	0,5				
2016-03-18T04:03:47.826	1,6	1,8				
2016-03-18T04:03:50.280	0,7	0,5				
2016-03-18T04:08:08.468	6,1	9,1	4,4	5,6	4,6	5,5
2016-03-18T04:09:06.766	6,5	8,1	7,4	5,5	4,9	6,0
2016-03-18T04:11:41.647	5,3	6,9	3,1	6,2	6,6	
2016-03-18T04:11:45.793	4,9	6,2	2,0	6,0	6,0	
2016-03-18T04:15:42.706	6,2	6,5	5,3	4,8	4,5	4,7

By regarding the WIM data set, we can obtain the weights we need for the comparison.

Table 8: Static weight (second row) compared with the WIM weight (bottom row).

ID	1	2	3	4	5	6	7	Total
2016-03-18T09:52:37.974+01:00	7,32			17,12			19,96	44,40
WIM 1740104(1)	6,2	3,9	4,6	4,3	5,5	5,1	5,4	35,00

This static weight data has to be typed in manually and can be time consuming if the sample sizes are big. For further use of this data, the Excel sheets, as seen in table 8, are saved as tabulator separated .txt files and can subsequently be used in other data processing programs, like MATLAB.

### 3.1.1. Weaknesses with this method

The method of collecting weight data by using a static weight and matching them with their WIM weights has some weaknesses. An occurring problem was that some vehicles had an assumed pause somewhere between the WIM site and the static weight, causing them to fall out of the vehicle weighing order. As an example, if we had first weighed a green truck at the traffic station, then another green one, which was followed by a red one, the order would be green-green-red. If we were to look at the video from one downstream WIM site to figure out the time at which they passed that site, and we were to find a vehicle order of green-red-green, that would make the identification more challenging. This incident can mean several things: The second green vehicle might have stopped for a short period and was surpassed by the red one before it was able to get back on the road again. Another explanation can be that the second green vehicle quit the road and a new green vehicle entered behind the red truck. As it was hard to determine what happened, we rejected a few such cases.

The video quality was also somewhat poor, which occasionally made it difficult to recognise certain vehicle characteristics like a small logo just above the driver's window. This could be solved by writing down more characteristics during the weighing at the traffic station, but this was sometimes difficult due to the weighing frequency. The vehicles came onto the scale weight, drove away quickly and then a new vehicle was on the weight.

A good method for improving these weaknesses would be to use automatic plate recognition. The number plates would be easily matched between the static weight and all the WIM sites, and the time used for manually matching them post-weighing would be drastically reduced. Unfortunately, such plate recognition data is, as mentioned above, not saved due to legal reasons,<sup>71</sup> and therefore we have to use our manual method.

Another weakness is the reproducibility of these results. Vehicles at the traffic station were not randomly sampled, implying that a representative sample might not be achieved. Obtaining the same data again might lead to different conclusions, for example different accuracy classes.

## 3.2. Data analysis

Most of the analysis of the data is done in MATLAB as this software is both quick and powerful with numerous pre-made statistical functions. Microsoft Excel has also been used, mostly for creating .txt files. They are subsequently imported into MATLAB in order to perform linear regressions, create histograms and box plots. The corresponding commands are mentioned below where they are relevant.

Some of the scripts used for the analysis is attached as attachment 2.

### 3.2.1. Errors

We want to know the relative error between the dynamic ( $W_d$ ) and static weights ( $W_s$ ) to see how much they deviate. The definition of the relative error is:

*Equation 1: Relative error*

$$\varepsilon = \frac{W_d - W_s}{W_s} * 100 \%$$

Furthermore, the mean and the standard deviation of the error can be calculated, which will be used to assess how accurate and precise the WIM registrations are.

The errors can also be plotted as a histogram by using the MATLAB function *histfit(data, nbins)* which is used for creating a histogram from the matrix *data* with *nbins* as the number of bins and then fit the data to a normal distribution.<sup>72</sup> In this way it is possible to see how the errors are distributed, if it is a normal distribution or a skewed distribution.

### 3.2.2. Linear regressions of measurements

The individual measurements can be plotted and a *linear regression*, that is a linear function fitted to the data using the method of least squares, can be performed to look at the general trend. Its MATLAB function is *polyfit(x,y,1)* which is used for polynomial curve fitting with in this case vectors *x* and *y* and a first-degree polynomial.<sup>73</sup> It subsequently returns all the terms of the obtained equations.

The fit function is on the form  $y = ax + b$ , where *y* represents the WIM weight, *x* the static weight, *a* the inclination term and *b* the constant term. If the system had no systematic or statistical errors, the data would lie on the line  $y = x$ .<sup>74</sup>



### 3.2.3. Calibration coefficients

In this task, I will also calculate some calibration coefficients  $C$ , which can be used to adjust the measured dynamic weights closer to the static weights. The adjusted static weight  $W_s$  can thus be calculated by multiplying the calibration coefficient  $C$  with the dynamic weight  $W_d$ :

*Equation 2: Adjustment of the dynamic weights.*

$$W_s = C * W_d$$

The COST 323 Final Report has several formulas for calculating the calibration coefficients depending on which repeatability and reproducibility conditions are present. All the conditions are described on page 16. For our conditions (R1) and (R2) the formula “1.c. Calibration on the mean square error (1)” has to be used.<sup>75</sup> The calibration coefficient  $C$  is given by:

*Equation 3: Calibration on the mean square error.*

$$C = \frac{\sum_i n_i W_{s_i}^2}{\sum_{i,k} W_{s_i} W_{d_{ik}}}$$

Where

$n_i$  = number of runs of the vehicle  $i$

$W_{s_i}$  = static gross weight of the vehicle  $i$

$W_{d_{ik}}$  = "dynamic" gross weight for the vehicle  $i$  and the run  $k$

As stated in citation 75, this method “minimises the mean square error of the individual gross weight measurements with respect to the static gross weights for all the vehicles passed, with the constraint that the “dynamic” gross weights are proportional to the static ones.”<sup>75</sup> The resulting linear fit will also pass through the origin.

I will also use another method from the same chapter in COST 323. This one is recommended for (r1), which we did not have, and gives a calibration coefficient when there is a mean bias (systematic error). Because of that this method is also interesting to look at, as it gives an unbiased estimator of the gross vehicle weight. The formula for “1.a. Calibration on the mean bias” is as follows<sup>75</sup> and it has the same parameters as the previous formula:

Equation 4: Calibration on the mean bias.

$$C = \frac{\sum_i n_i}{\sum_{i,k} \left( \frac{W d_{ik}}{W s_i} \right)}$$

I will perform the two analyses later in this thesis and look at which method that improves our dynamic weight estimation the best. It is however important to notice that these methods are only recommended for gross vehicle weight and not for other axle combinations. Thus, the calibration coefficients cannot be used for all our axle combinations.

### 3.2.4. How to Calculate the Confidence Level

The confidence level  $(1-\alpha)$  describes how often an individual value of the relative errors, with a sample mean  $m$  and standard deviation  $s$ , falls within a centered confidence interval of  $[-\delta, \delta]$  when a population is sampled on many occasions.<sup>76,77</sup>

Thus, we want to calculate the probability  $\pi$  for the level of significance being higher than a required value  $\pi_0$  in order to assess the corresponding accuracy class from COST 323.  $\pi$  depends on the test conditions, the environmental test conditions and the sample. If  $\pi > \pi_0$  then the measurements are accepted in the accuracy class with the specified  $\delta$  (see COST 323 table in the WIM section).<sup>78</sup>

A Student t-distribution is used when we want to estimate the means of a normally distributed population, in which the sample size is small and standard deviations is unknown.<sup>79</sup> This is in our case necessary as our sample sizes are small and we do not know the standard deviations. COST 323's chapter 11.4.6.1 states how the calculations are performed:

Equation 5: Estimated level of confidence calculated from cumulative distribution function of a Student variable.

$$\pi = \Phi(u_1) - \Phi(u_2)$$

where

Equation 6: Variable  $u_1$ .

$$u_1 = \frac{\delta - m}{s} - \frac{t_{n-1;\alpha/2}}{\sqrt{n}}$$

and

Equation 7: Variable  $u_2$ .

$$u_2 = \frac{-\delta - m}{s} + \frac{t_{n-1;\alpha/2}}{\sqrt{n}}$$

With the following variables:

$$\alpha = 0,05$$

$t_{n-1;\alpha/2}$  = critical t value of a two-tailed t-test with n-1 degrees of freedom

$m$  = mean of the error

$s$  = standard deviation of the error

$n$  = sample size

$\alpha = 0,05$  is given in COST 323 manual and is the significance level, which is the probability of rejecting the null hypothesis when it is actually true. It is also called a type I error and is also used to find the critical t-value.<sup>80</sup>

### 3.2.5. Box plots

Box plots are a great way of illustrating how a set of data is distributed by the use of quartiles (rank-ordered data set divided into four equal parts).<sup>81</sup> They are also good for interpreting how the spread of the data is, by looking at minimum and maximum values, as well as seeing if the distribution is skewed or not.<sup>82</sup>

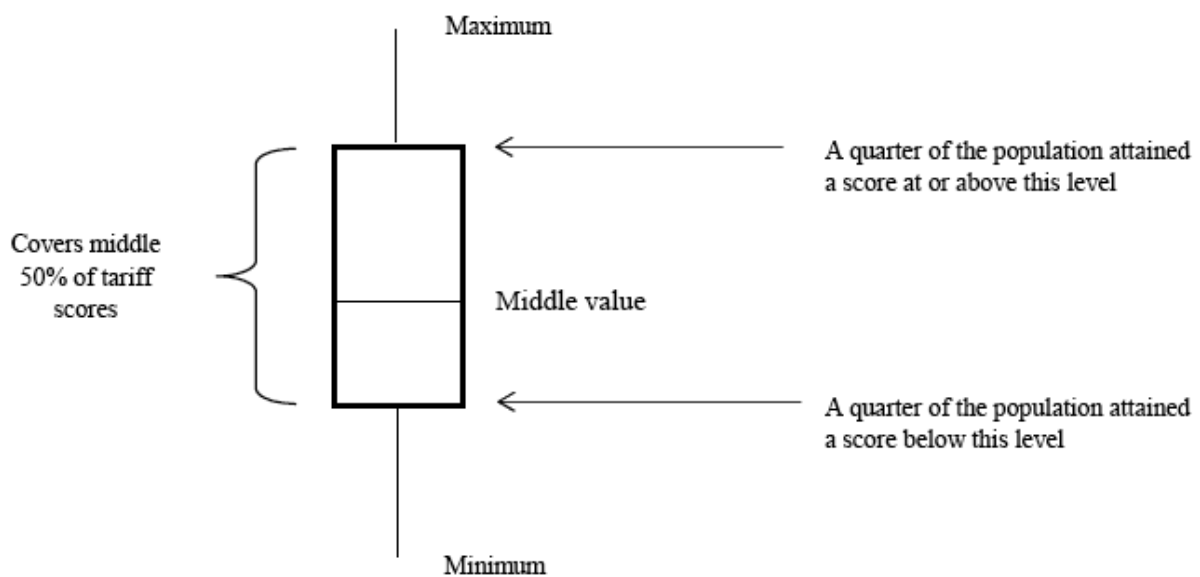


Figure 16: Box plot explained with an example of scores. Figure: The Scottish Government.<sup>83</sup>

In figure 16, we can see a minimum and a maximum value, represented by the bottom and top whiskers (the thin lines). The box in which the middle value lays, covers 50 % of the measurements and is called the interquartile range (IQR). It is delimited by the 1<sup>st</sup> quartile (Q1) below which a quarter of the data lays and 3<sup>rd</sup> quartile (Q3) above which a quarter of the data lays. The placement of the median tells us if the distribution is skewed or not. In figure 13 it can be seen that the middle value is not aligned in the middle of the IQR, but a bit towards the minimum, which means it is skewed to the right. Any extreme values (outliers) that occur will end up as separate dots outside of the minimum-maximum range.

The distance from Q1 to the minimum value or Q3 to the maximum value is 1,5 x IQR. Outliers lay either 3 x IQR or more above the 3<sup>rd</sup> quartile or 3 x IQR or more below the first quartile.<sup>84</sup>

A box plot can tell us if the data set is symmetric or not, but it cannot tell us the shape of the distribution as a histogram can.<sup>85</sup> However, this is not a concern for us because we are mostly interested in the spread and center, which can be found directly from a boxplot.

Some general observations that can be made about box plots are if the box is comparatively short or tall, if one box plot is higher than another, uneven sizes of IQRs and min-max ranges and comparisons in cases with identical medians but different distributions.<sup>86</sup>

The corresponding MATLAB function is *boxplot(x)* which is used for creating box plots with the data from *x*.<sup>87</sup>

### 3.2.6. Box plots and methods for testing statistical significance

In hypothesis 2, we want to look at the time-dependent effects on the WIM systems. To see if the errors remain stable over time, the data has to be tested for statistical significance. Consequently, we want to examine whether the data has changed, and in that case, if the difference is statistically significant.

R. McGill, J. Tuket and W. Larsen (1978) have written about a method for visual inspection if medians are statistically different by using notched box plots (see figure 17). The notches are the constriction at both sides of the red median line. If the notches of two box plots do not overlap, the difference of the medians is roughly statistically significant at a confidence level of 95 %.<sup>88</sup>

In figure 17, it can be clearly seen that the notches in box plot 1 and box plot 2 do not overlap. Box plot 1's bottom notch ends at around - 11 %, whereas box plot 2's top notch ends at - 15 %. The difference of medians can therefore be said to be statistically significant with a confidence level of 95 %.

If there are difficulties in seeing if notches overlap or not, their 95 % confidence intervals have to be calculated, e.g. by using computer programmes. An easier method is to conduct traditional hypothesis testing.

When hypothesis H1 is examined, that is if there is a difference between the dynamic and static weights, a paired sample t-test has to be used. Such a t-test, often referred to as Student's t-test, is used to determine if two sets of data have a significantly difference when the sample sizes are small.

The reason for this is that the sample from our first population is related to the corresponding sample from our second population, i.e. the dynamic weight has a corresponding static weight. By using MATLAB's pre-made command `ttest`, a paired-sample t-test, we can quickly check for statistical significance. When using this command with a test decision,  $h = ttest(x,y)$ , it tell us if the null hypothesis, i.e. that the data in x and y comes from a normal distribution with a mean equal to zero and unknown variance, is rejected or not.<sup>89</sup> In other words, if the data comes from the *same* distribution.

h results in either  $h = 0$ , i.e. the null hypothesis is not rejected, or  $h = 1$ , i.e. the null hypothesis is rejected at the default 5 % significance level.<sup>90</sup> I will be using the same significance level,  $\alpha = 0,05$ , as this has been previously suggested as a level by COST 323. This is also the default value in the MATLAB commands.

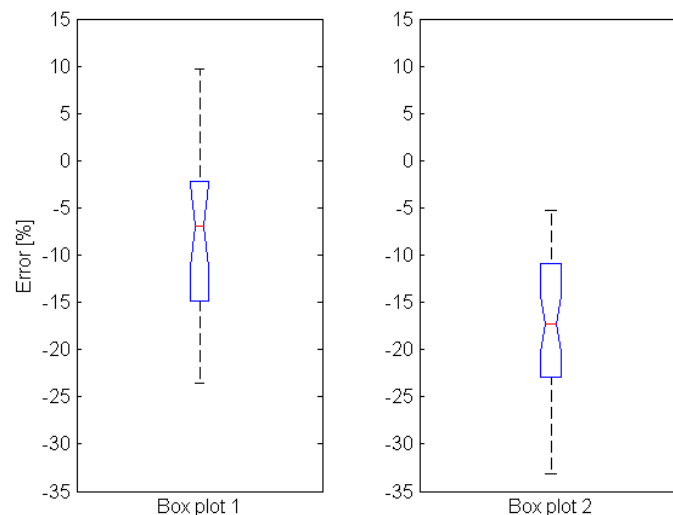


Figure 17: Example of two box plots with non-overlapping notches. The red line represents the median. Made with MATLAB.

By using the command  $[h, p] = ttest(x,y)$  we can get the probability value p, also known as the p-value. This is the probability of obtaining a result at least as extreme as what we acquired in our dataset, with the assumption of a true null hypothesis.<sup>91</sup> In other words, whereas  $\alpha$  tells how extreme the data has to be before the null hypothesis can be rejected, the p-value tells us how extreme the data actually is. Thus, if the p-value is less than or equal to  $\alpha$ , which is 0,05, we can reject the null hypothesis.<sup>92</sup>

Hypothesis H2, in which we examine the time-dependent changes, requires an independent two-sample t-test since two different data sets from different WIM sites are compared.

MATLAB's corresponding command is  $h = ttest2(x,y)$  and returns a test decision for the null hypothesis at a 5 % significance level. As in the previous test,  $h = 1$  means that it is rejected, while  $h = 0$  means failed to reject.<sup>93</sup>

Hypothesis H3 requires us to test many means since several WIM sites are compared to different axle combinations. If we want to test three or more means and examine whether they are equal or not, we can use the statistical method of one-way analysis of variance (ANOVA) which uses the F-distribution.<sup>94</sup> ANOVA one-way testing is used when there is one factor (a characteristic that labels the population), i.e. static weight, with several levels of the factor,<sup>95</sup> i.e. different WIM sites.

When the null hypothesis is rejected using ANOVA, it leads to the conclusion that all group means are not the same. However, this result does not tell us which group means that are different. Performing multiple t-tests to figure out which of the pair means that are significantly different is not recommended. The reason for this is that the numerous t-tests will increase the probability of incorrectly rejecting the null hypothesis and not stay at the default alpha value 0,05.<sup>96</sup> Therefore we must examine the means by using ANOVA.

MATLAB's ANOVA function is  $p = anova1(y)$  and returns the p-value for a balanced one-way ANOVA. Since our samples are unbalanced, i.e. every sample has a different size, the *group* input argument has to be used.<sup>97</sup>

The command also presents the results graphically, so that it can be seen which 95 % confidence intervals that overlap. This way we can see if errors for some axle combinations are similar to other axle combinations.

## 4. Results

### 4.1. Criteria for data selection

As a short summary of the WIM sites, 1740009 was the westmost site and 1740104(1) was the eastmost site close to Åsen during the measurement on 11/11-2015. 1740104(2) was the same site as the latter, but at a different date: 18/3-2016. 540032 was the northmost site of the section control TEC close to Otta, while 540031 was the southmost. 540109 laid south of Otta. Their date was 27/4-2016.

After the data collections, we were not able to use every vehicle that we weighed at the traffic station for further analysis. Sometimes vehicles were only registered at the WIM sites, but not at the traffic station, probably due to a route choice that did not go by the traffic station. E.g. at Åsen there is a road to Sweden between WIM 1740009 and the traffic station that drivers may have chosen. The opposite incident of this also happened; no WIM weight, but only static weight at the traffic station was registered. This can be caused by malfunctioning WIM registrations, which though rarely happens, or that the driver came from a road that did not pass any of the nearby WIM sites (1740104 and 1740009). The affected data to which this happened was subsequently discarded.

Other times, vehicles registered by the WIM system at the section control TEC sites had a different amount of axles between the two sites. E.g. one vehicle was registered with five axles at WIM1740104 and with six axles at WIM1740009. Mismatched number plates, drivers who put down one more axle between the sites (many heavy trucks have several extra wheel sets that can be used) or a misregistration by the WIM systems, can cause this. To continue the previous example, if we had the static load from the exemplified vehicle, we only discarded the WIM measurement that did not have the same amount of axles as at the traffic station, so that the data from only one WIM was used. I.e. if the vehicle had six axles at the traffic station, only the data from WIM 1740009 would be used for comparison.

After the completion of the data acquisitions, we have seen that most of the weighed vehicles at the traffic station were vehicles with six axles, followed by those with five axles. Other axle combinations, such as vehicles with two, three, four and seven axles, have had a limited presence on the road and have thus not been weighed that much. This has resulted in very few samples of certain vehicles. Therefore, only the results from the six and five axle vehicles are included as they were most prominent.

Also, no outliers have been removed from the data sets. The reason for this is to ensure a calculation of the real system performance of WIM.

#### 4.1.1. Results from the 1<sup>st</sup> data acquisition

Data was collected on highway E6 Åsen on 11/11-2015. Both WIM sensors 1740009 and 1740104 were operative and used for our data collection. We had placed one camera at each site to record the vehicles when they passed them. As those two WIMs are a section control WIM, it was only necessary to watch the videos from one site. At this very day, the skies were cloudy and it rained a bit. 119 vehicles were weighed that day at the traffic station, from which 82 (69 %) was chosen for further analysis.

#### 4.1.2. Results from the 2<sup>nd</sup> data acquisition

On 18/3-2016, data was collected on highway E6 Åsen, the same place with the same WIM sensors as the first time. Unfortunately, we encountered a hurdle as WIM 1740009 site stopped functioning during the winter. This day 81 vehicles were chosen for further analysis. The causes are currently unknown, though winter and ice wear may play a role. Because of this, only the results from WIM 1740104 (WIM 1740104(2)) are presented. The failure of WIM 1470009 means that the comparison to the last respective measurement in November 2015, as stated in hypothesis H2, is not performed. Otherwise, everything is done as usual.

#### 4.1.3. Results from the 3<sup>rd</sup> data acquisition

On 27/4-2016, more data was collected on the road E6 close to Otta. This day 192 vehicles were chosen for further analysis.

We had four cameras filming five different WIM sites, two of which were section control TECs. Since the data from those two points is aggregated by the automatic plate recognition system, there was only need for one camera filming at the endmost section control TEC.

When we were collecting the WIM data from the system two days later, we realised that one of the WIM sites was not operative on that day. We also saw that the data from the endmost WIM on Vinstra was flawed, in which the data showed a high amount of 8 axle vehicles and many axle weights of 0,2 tonnes. As we didn't weigh any vehicles with more than 7 axles, nor had any static axle loads of 0,2 tonnes, we assumed that the data was faulty and subsequently discarded the data from both those WIMs.

It is difficult to know exactly why the data was flawed. Bjørn Brændshøi, one of the technicians working with WIM at NPRA, said that the system probably works fine, but that the road and ground conditions negatively affect the registration. Heavy vehicles might create additional pressure waves through the pavement, which can create those 0,2 tonnes that frequently showed up.<sup>98</sup>



## 4.2. General plots of the dynamic and static weights

In the following figure, we can see the weights for every vehicle that was statically weighed and to which we found a corresponding WIM weight. The p-values, which is the probability that the dynamic weights are the same as the static weights, are written in the bottom right corner.

### 4.2.1. All axles, GVW

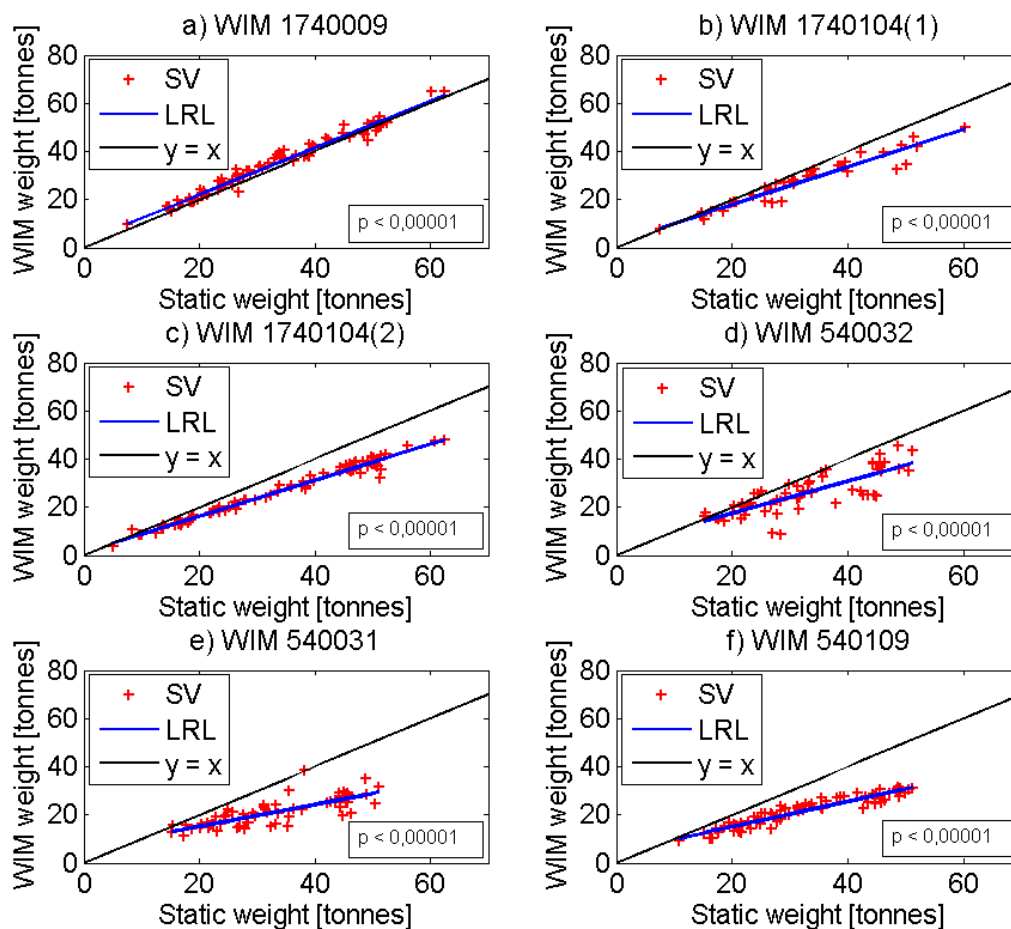


Figure 18: GVW of all axle vehicles. SV = Single values. LRL = Linear regression line,  $p$  = probability that there is no difference between the dynamic and static weights.

In figure 18, we see that all the WIM weights generally are too low compared to the static loads, except of a). This can be seen when the measurements are below the line of  $y = x$ . The p-values are also quite low, thus indicating a significant difference between WIM weights and the static weights. They are related to our hypothesis H1.

The best data can be found in a) in which the accuracy and precision is quite high. b) has an ok precision, but not so accurate measurements as the inclination term of the linear regression

is different from the  $y = x$  line. Furthermore, c) seem to resemble the latter quite a lot in terms of inclination of the LRL, whereas d) is dissimilar. The data is more spread out and is therefore not so precise. e) looks even worse than WIM 540032, as the inclination term of the linear regression has an even lower value. However, the measurements in f) are precise but not so accurate. In general, every subplot except of a) shows a significant systematic error.

#### 4.2.2. Six axles, GVW

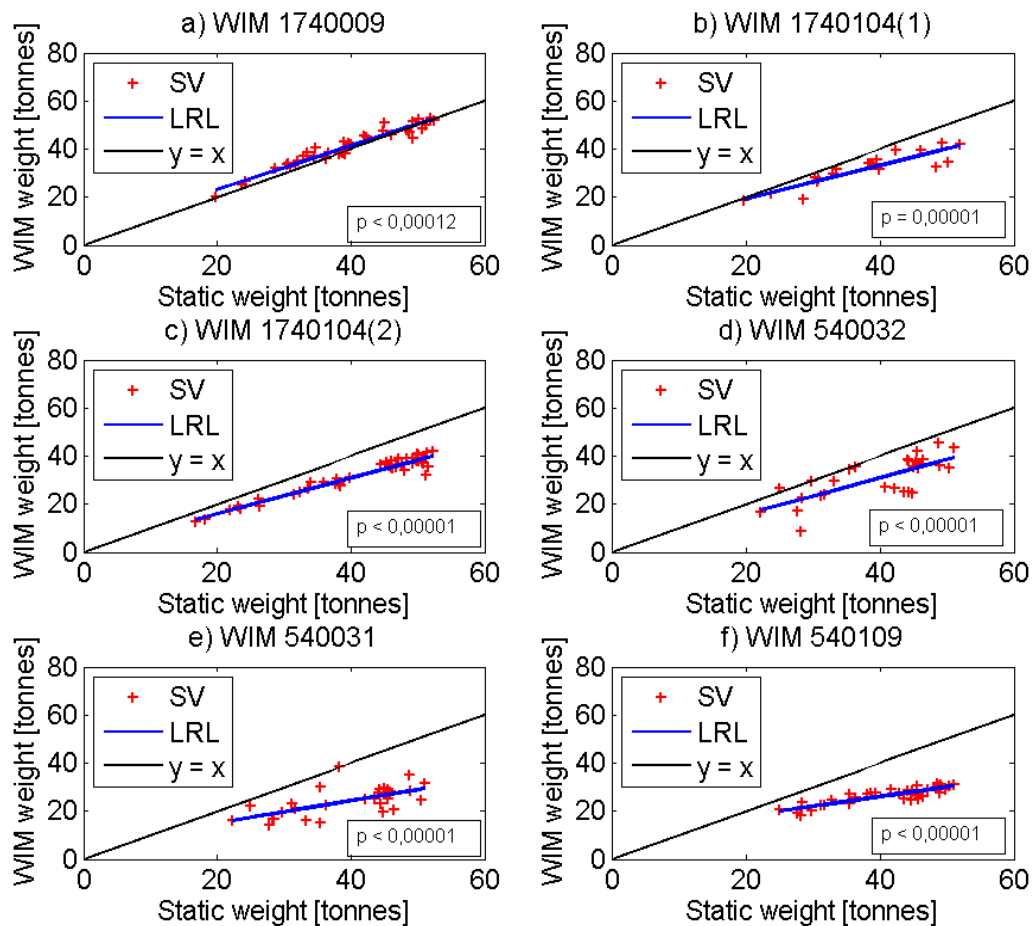


Figure 19: GVW of six axle vehicles. V = Single values. LRL = Linear regression line,  $p$  = probability that there is no difference between the dynamic and static weights.

In figure 19, we can see that the results vary a lot depending on which WIM site is regarded. The LRL of a) has visibly the best fit and its data has the highest p-value, but it is still small enough to indicate a significant change ( $p < 0,05$ ). At c) we can see that a lot of vehicles are clustered together at the end of the linear regression line. This means that many vehicles from that day had a high gross vehicle weight. f) has very precise measurements, while this is not the case for e). All the p-values are below the significance level.

#### 4.2.3. Six axles, front axle

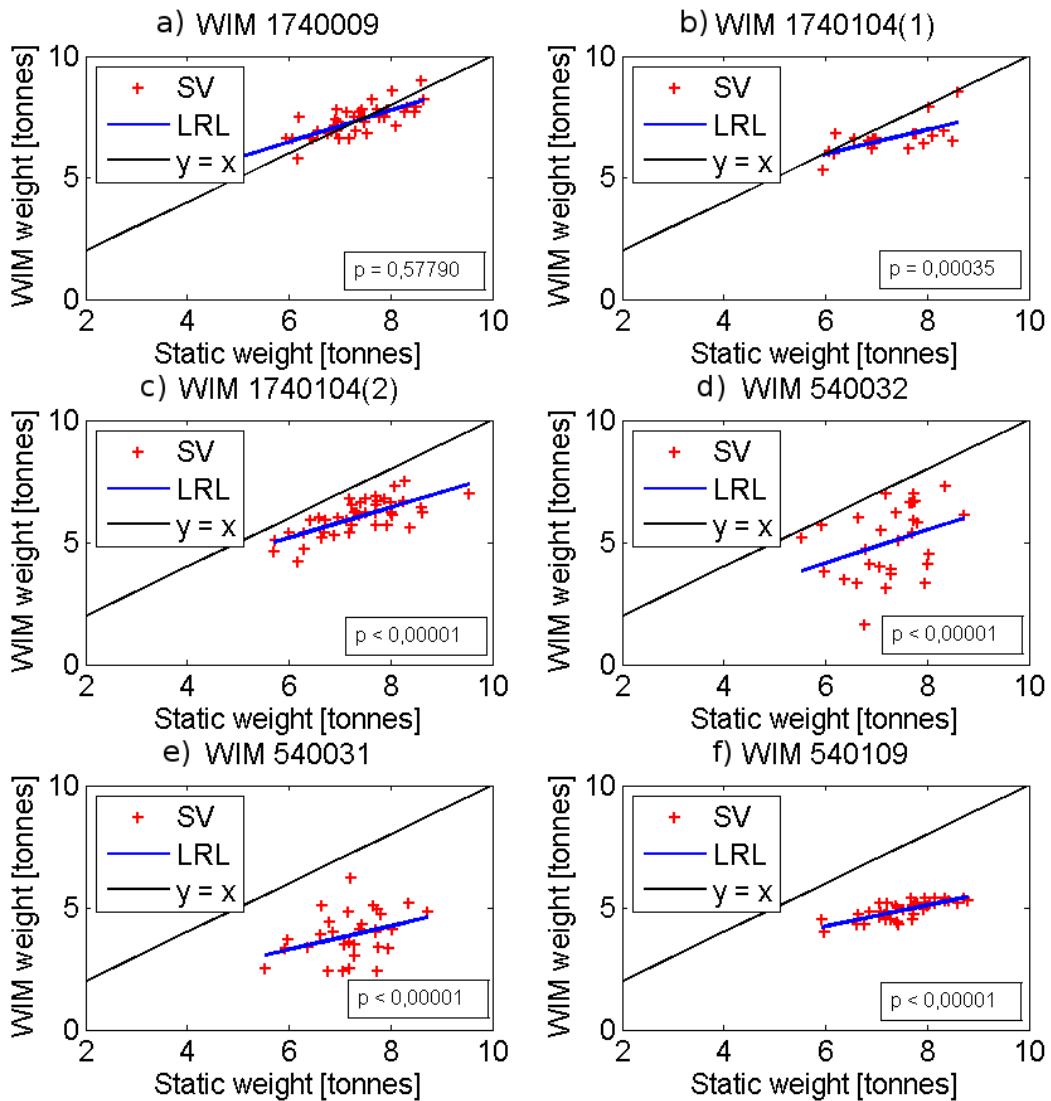


Figure 20: Front axle weight of six axle vehicles. SV = Single values. LRL = Linear regression line,  $p$  = probability that there is no difference between the dynamic and static weights.

When regarding figure 20, we can see that a) has the highest p-value ( $p = 0,57790$ ), which indicates that there is no significant difference between the WIM and the static weights. b) has some spread in the data, while c) also shows some spread in its data and is not so accurate. d) is however not very precise nor very accurate. e) seems to fit the  $y = x$  line even worse than the latter, while f) has quite precise measurements but with large systematic errors. All the WIM sites except of a) show too low WIM weights.

#### 4.2.4. Six axles, 2<sup>nd</sup> and 3<sup>rd</sup> axles

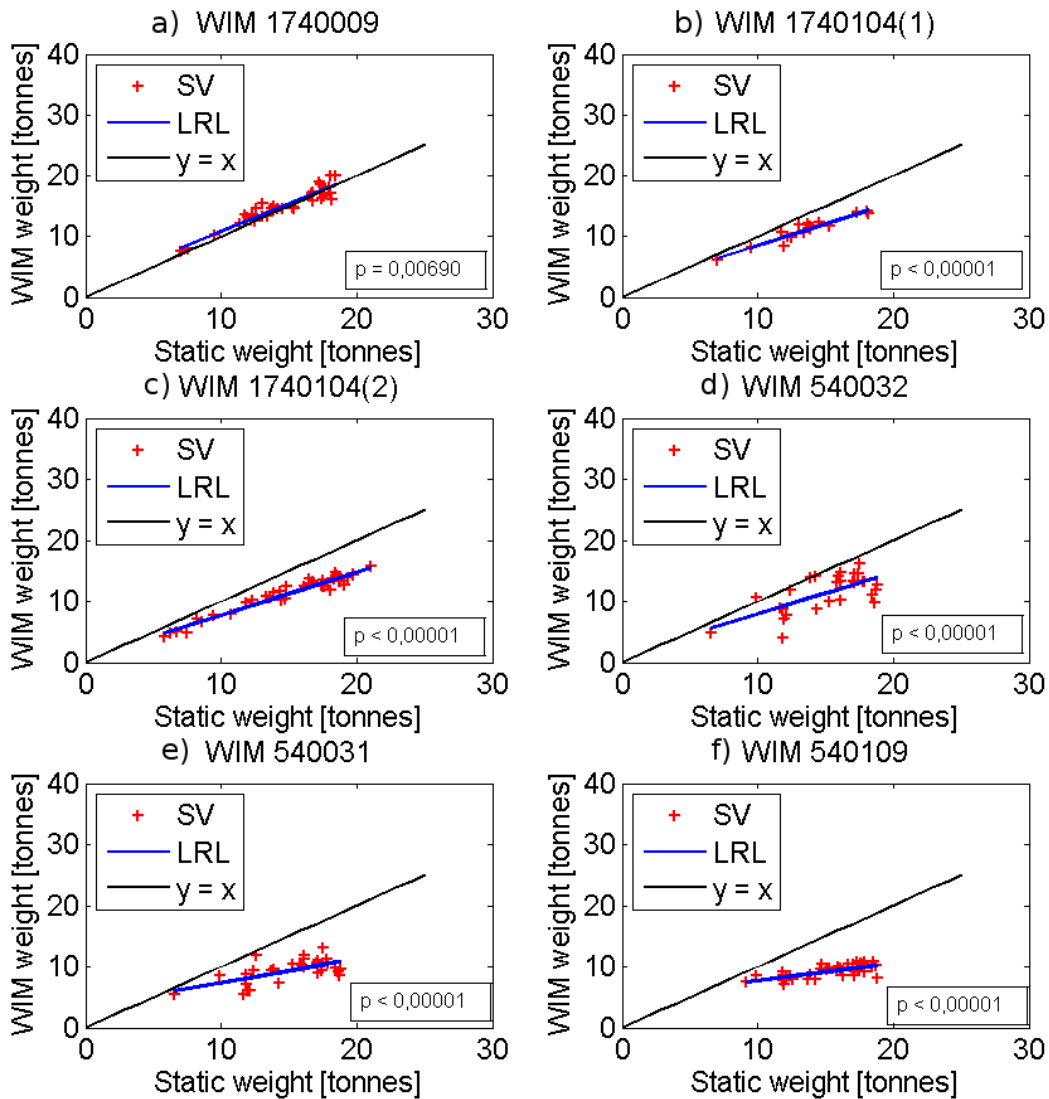


Figure 21: 2<sup>nd</sup> and 3<sup>rd</sup> axles' weight of six axle vehicles. SV = Single values. LRL = Linear regression line,  $p$  = probability that there is no difference between the dynamic and static weights.

In this figure, we can see that the weight range is more limited because only two axles are considered. It can also seem like the results from a), b) and c) are a lot more accurate and precise than in the previous figures. d) has some spread in its data, the same goes with e), but not for f). The latter is, like the three previous figures, not so accurate but still precise. The p-values show that all the differences are statistically significant.

#### 4.2.5. Five axles, GVW

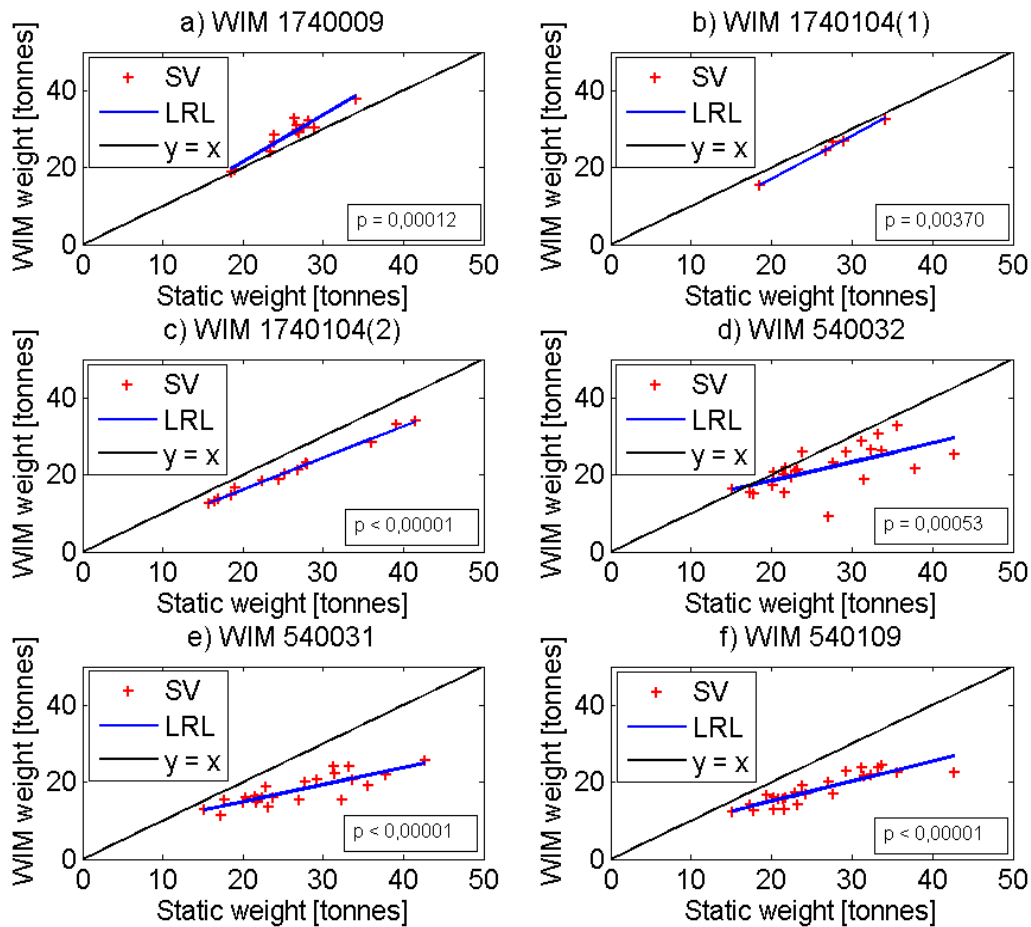


Figure 22: GVW of five axle vehicles. SV = Single values. LRL = Linear regression line,  $p$  = probability that there is no difference between the dynamic and static weights.

In figure 22, we can notice that a) and b) do not have very large sample sizes due to their few measurements (red crosses). They are also quite accurate, which means they fit the  $y = x$  line quite well. c) is somewhat inaccurate, but its LRL's inclination term (0,82) is not that different from  $y = x$ . d) fits the line poorly and is not very precise, which is also the case for e). f) is less precise than it used to be in the previous figures, which can indicate that this WIM site is worse when the GVW of six axle vehicles are examined. We can see that the largest p-value is found in b), but it is still not larger than over significance level ( $\alpha = 0,05$ ).

### 4.3. P-values and hypotheses testing

Table 9: P-values and hypothesis H1 testing results for different axle combinations.

<b>ALL AXLES</b>				
	<b>WIM site</b>	<b>Combination</b>	<b>p</b>	<b>h</b>
1)	1740009	GVW	< 0,00001	1
2)	1740104(1)	GVW	< 0,00001	1
3)	1740104(2)	GVW	< 0,00001	1
4)	540032	GVW	< 0,00001	1
5)	540031	GVW	< 0,00001	1
6)	540109	GVW	< 0,00001	1
<b>SIX AXLES</b>				
	<b>WIM site</b>	<b>Combination</b>	<b>p</b>	<b>h</b>
7)	1740009	GVW	0,00012	1
8)	1740104(1)	GVW	0,00001	1
9)	1740104(2)	GVW	< 0,00001	1
10)	540032	GVW	< 0,00001	1
11)	540031	GVW	< 0,00001	1
12)	540109	GVW	< 0,00001	1
<b>SIX AXLES</b>				
	<b>WIM site</b>	<b>Combination</b>	<b>p</b>	<b>h</b>
13)	1740009	Front axle	0,57790	0
14)	1740104(1)	Front axle	0,00035	1
15)	1740104(2)	Front axle	< 0,00001	1
16)	540032	Front axle	< 0,00001	1
17)	540031	Front axle	< 0,00001	1
18)	540109	Front axle	< 0,00001	1
<b>SIX AXLES</b>				
	<b>WIM site</b>	<b>Combination</b>	<b>p</b>	<b>h</b>
19)	1740009	2nd + 3rd axle	0,00690	1
20)	1740104(1)	2nd + 3rd axle	< 0,00001	1
21)	1740104(2)	2nd + 3rd axle	< 0,00001	1
22)	540032	2nd + 3rd axle	< 0,00001	1
23)	540031	2nd + 3rd axle	< 0,00001	1
24)	540109	2nd + 3rd axle	< 0,00001	1
<b>FIVE AXLES</b>				
	<b>WIM site</b>	<b>Combination</b>	<b>p</b>	<b>h</b>
25)	1740009	GVW	0,00012	1
26)	1740104(1)	GVW	0,00370	1
27)	1740104(2)	GVW	< 0,00001	1
28)	540032	GVW	0,00053	1
29)	540031	GVW	< 0,00001	1
30)	540109	GVW	< 0,00001	1

In table 9, the p-values show the probability that the null hypothesis of H1 is true, which is that there is no difference between the WIM weights and the static weights.  $h = 1$  means that hypothesis  $a_0$  is rejected,  $h = 0$  means that it was not rejected.

Furthermore, we can see that all null hypothesis, except of 13), have been rejected. This combination has a p-value of 0,57790, that means a 57,79 % chance that the null hypothesis is true. This percentage is not lower than our alpha value of 0,05, thus it cannot be rejected.

The second highest p-value can be found at 19), but this value is smaller than 0,05 and the null hypothesis is therefore rejected.

In general, we can see from table 9 that most p-values are very low, indicating a small probability that the null hypotheses are true. This means that there is no good correspondence between the WIM weights and the static weights. Thus, hypothesis H1 must be rejected.

In table 10, a general overview of different axle combinations with their sample sizes, linear regression equations (LRE), errors and accuracy classes can be seen. From the LRE column we can see that 1) had the most accurate inclination term (0,98) compared to  $y = x$  (having an inclination term of exactly 1). We could see this good fit in figure 18 a). The worst inclination term found was 0,27 from row 18), see figure 21 f). In general, the constant terms vary from -5,00 to 9,98, with almost none around zero.

By looking further at the different WIM sites in table 10, we can see that the LRE's constant terms from WIM 540032, 540031 and 540109 are large when the gross vehicle weight is considered. Also, the inclination terms are overall lower than the other WIM sites. This leads to a poor accuracy and reaches only accuracy class E.

It is also important to notice that the linear regression lines are only valid within their own ranges limited by their data. Therefore, the regression lines cannot describe new data outside of the ranges.

When looking at the mean and standard deviation of the errors, we can see that the mean error spans from -46,21 % to 1,09 % for the front axle of six vehicles. This means that most of the errors are negative, which is also the case with the remaining axle combinations. This indicates that the WIM weight in general is too low, something that can be seen by looking at the figures 18 to 22. The linear regression line is below the  $y = x$  line most of the time, thus the WIM weights are generally biased towards underestimation. The standard deviations of the errors from all the axle combinations go from 2,6 % to 18,96 %. This indicates a highly varying precision of the different WIM sites.

By having a look at the calculated accuracy classes we can see that WIM 1740009 in general has obtained the best classes compared to the other sites. Its best-obtained class is B, seen in table 10, row 19), while its worst is class D, seen in 25). At the end of that spectrum, we find WIM 540032, 540031 and 540109. They all have class E with every possible axle combination and are thus the worst WIM sites concerning accuracy. The remaining rows have either class C, D+ or D.

Table 10: General overview of the sites and the axle combinations. *n* = sample size, *LRE* = Linear regression equation, *SD* = standard deviation, *A.C* = accuracy class from COST 323.

<b>ALL AXLES</b>							
	<b>WIM site</b>	<b>Combination</b>	<b>n</b>	<b>LRE</b>	<b>Mean error [%]</b>	<b>SD. error [%]</b>	<b>A.C.</b>
1)	1740009	GVW	82	$y = 0,98x + 2,53$	6,67	7,66	D+
2)	1740104(1)	GVW	40	$y = 0,78x + 2,30$	-13,1	9,03	D
3)	1740104(2)	GVW	81	$y = 0,75x + 1,30$	-19,86	6,76	E
4)	540032	GVW	57	$y = 0,67x + 4,13$	-18,73	17,15	E
5)	540031	GVW	59	$y = 0,46x + 6,20$	-33,49	13,14	E
6)	540109	GVW	76	$y = 0,53x + 4,63$	-31,7	8,11	E
<b>SIX AXLES</b>							
	<b>WIM site</b>	<b>Combination</b>	<b>n</b>	<b>LRE</b>	<b>Mean error [%]</b>	<b>SD. error [%]</b>	<b>A.C.</b>
7)	1740009	GVW	40	$y = 0,90x + 5,28$	4,48	5,82	C
8)	1740104(1)	GVW	20	$y = 0,69x + 5,73$	-14,61	8,44	D
9)	1740104(2)	GVW	42	$y = 0,74x + 1,26$	-22,39	4,36	E
10)	540032	GVW	29	$y = 0,77x + 0,32$	-22,26	16,19	E
11)	540031	GVW	30	$y = 0,46x + 6,02$	-37,93	12,91	E
12)	540109	GVW	39	$y = 0,40x + 9,98$	-34,37	7,06	E
<b>SIX AXLES</b>							
	<b>WIM site</b>	<b>Combination</b>	<b>n</b>	<b>LRE</b>	<b>Mean error [%]</b>	<b>SD. error [%]</b>	<b>A.C.</b>
13)	1740009	2nd + 3rd axle	35	$y = 0,91x + 1,85$	4,03	6,83	C
14)	1740104(1)	2nd + 3rd axle	17	$y = 0,71x + 1,50$	-17,51	5,85	D+
15)	1740104(2)	2nd + 3rd axle	40	$y = 0,70x + 0,79$	-24,29	5,24	E
16)	540032	2nd + 3rd axle	28	$y = 0,67x + 1,32$	-24,06	16,22	E
17)	540031	2nd + 3rd axle	29	$y = 0,40x + 3,44$	-36,39	12,46	E
18)	540109	2nd + 3rd axle	38	$y = 0,27x + 5,11$	-38,56	8,51	E
<b>SIX AXLES</b>							
	<b>WIM site</b>	<b>Combination</b>	<b>n</b>	<b>LRE</b>	<b>Mean error [%]</b>	<b>SD. error [%]</b>	<b>A.C.</b>
19)	1740009	Front axle	40	$y = 0,65x + 2,62$	1,09	7,28	B
20)	1740104(1)	Front axle	35	$y = 0,50x + 2,98$	-8,27	8,29	C
21)	1740104(2)	Front axle	42	$y = 0,62x + 1,48$	-17,64	7,01	D
22)	540032	Front axle	29	$y = 0,68x + 0,05$	-30,76	18,96	E
23)	540031	Front axle	30	$y = 0,48x + 0,44$	-46,21	12,5	E
24)	540109	Front axle	39	$y = 0,43x + 1,64$	-34,75	4,04	E
<b>FIVE AXLES</b>							
	<b>WIM site</b>	<b>Combination</b>	<b>n</b>	<b>LRE</b>	<b>Mean error [%]</b>	<b>SD. error [%]</b>	<b>A.C.</b>
25)	1740009	GVW	13	$y = 1,22x - 2,81$	10,37	6,69	D
26)	1740104(1)	GVW	5	$y = 1,11x - 5,00$	-8,33	5,14	A
27)	1740104(2)	GVW	15	$y = 0,82x - 2,56$	-18,67	2,6	D
28)	540032	GVW	23	$y = 0,48x + 8,82$	-16,04	17,51	E
29)	540031	GVW	23	$y = 0,45x + 6,04$	-31,02	10,26	E
30)	540109	GVW	24	$y = 0,52x + 4,69$	-28,57	8,02	E



#### 4.4.Errors of axle combinations when one WIM site is regarded

In this section, the errors between the WIM weights and static weights are shown in percent as a box plot. This way it is easy to assess how the errors change depending on which WIM site or axle combination is considered. The following section shows how the combinations vary at one WIM site.

##### 4.4.1. WIM 1740009, 11/11-2016

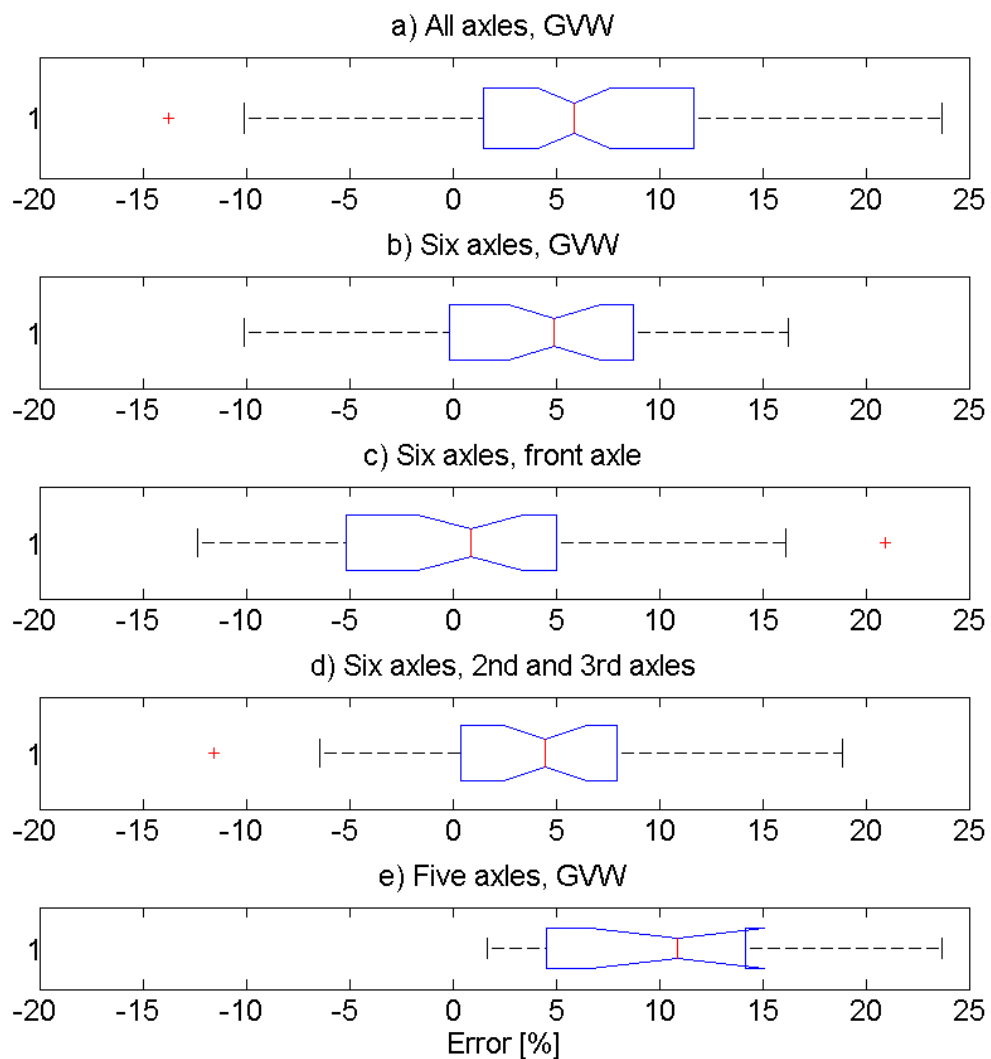


Figure 23: Errors from WIM 1740009.

In figure 23, we can see that the medians, i.e. the red lines, of a), b) and d) are centered about 5 %, but has uneven distribution by looking at the IQR's centre and whiskers. e) has the greatest median, while c) has the lowest. It can also be seen that none of the errors have a

median below 0 %. This means that more than 50 % of the errors are positive. The box plots with the smallest interquartile range (IQR) seem to be b) and d), telling us that most data fall within this small range. c) has a larger IQR and thus the data is spread out a bit more.

4.4.2. WIM 1740104(1), 11/11-2016

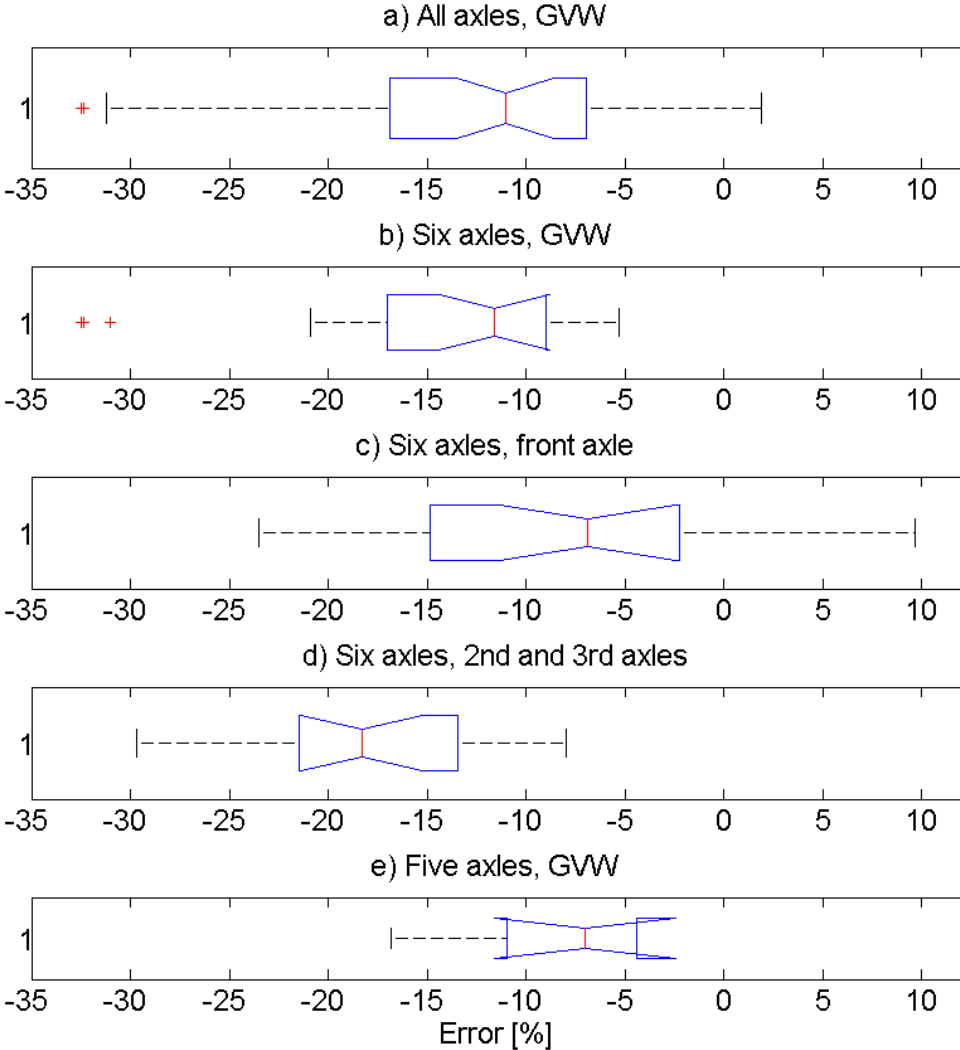


Figure 24: Errors from WIM 1740104(1), the first measurement at WIM 1740104.

The first thing that can be seen in figure 24 is that all box plots have medians that are below 0 %. This means that all the WIM weights in general are too low compared to the static weights. The box plots' ranges vary a lot and whereas a) has a min-max range of about 33 %, e) only has a range of about 13 %. Furthermore, we can see that the errors are depending on which combination is looked at. d) has the worst accuracy.

4.4.3. WIM 1740104(2), 18/3-2016

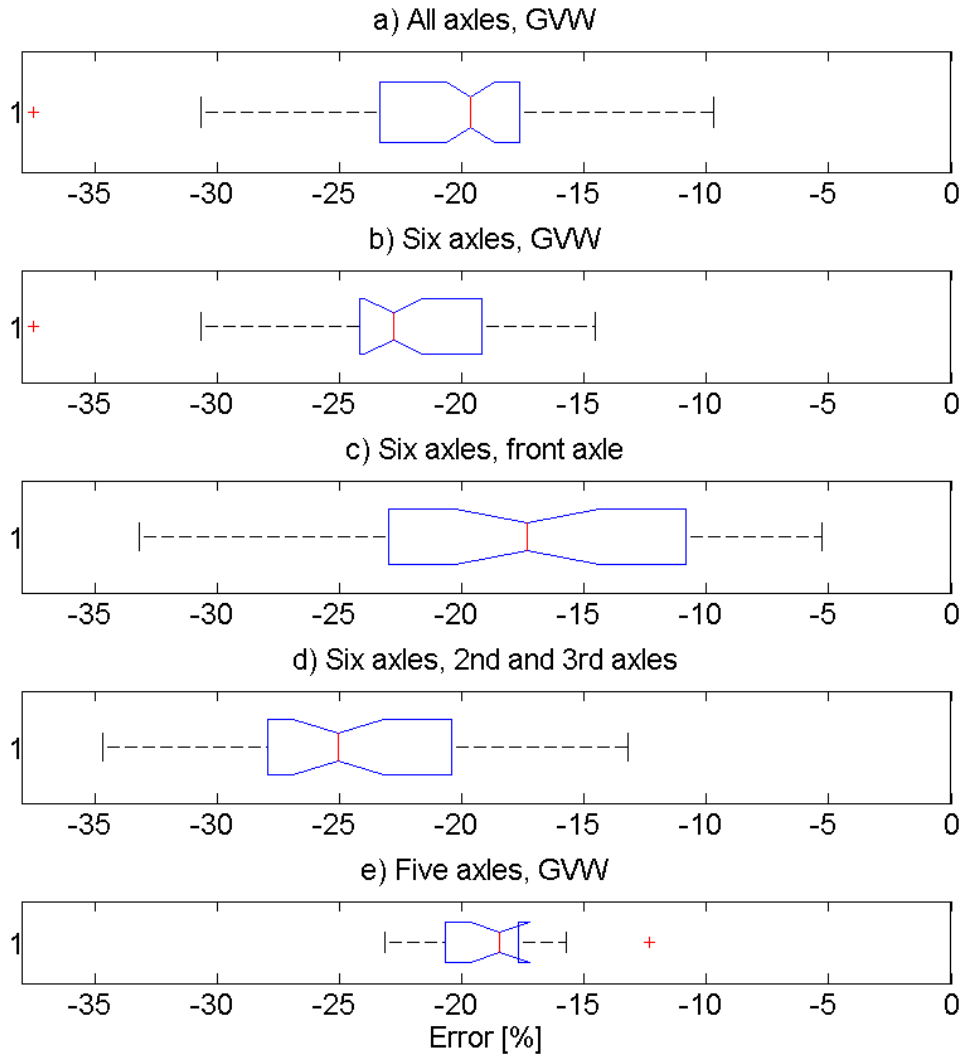


Figure 25: Errors from WIM 1740104(2), the second measurement at WIM 1740104

As in the previous figure, figure 25's medians are all negative, whose values lay between -16 % to -25 %. e) has the narrowest min-max range, whereas c) has the greatest. This is also the case when the inter-quartile ranges (IQR) are compared. The findings imply that most of e)'s values fall within a short range and that the opposite is true for c). It can also be seen that both a) and b) are highly skewed distribution, as their medians are not centered in the IQR. Here we can also see that the errors depend on which axle combination is looked at.

#### 4.4.4. WIM 540032, 27/4-2016

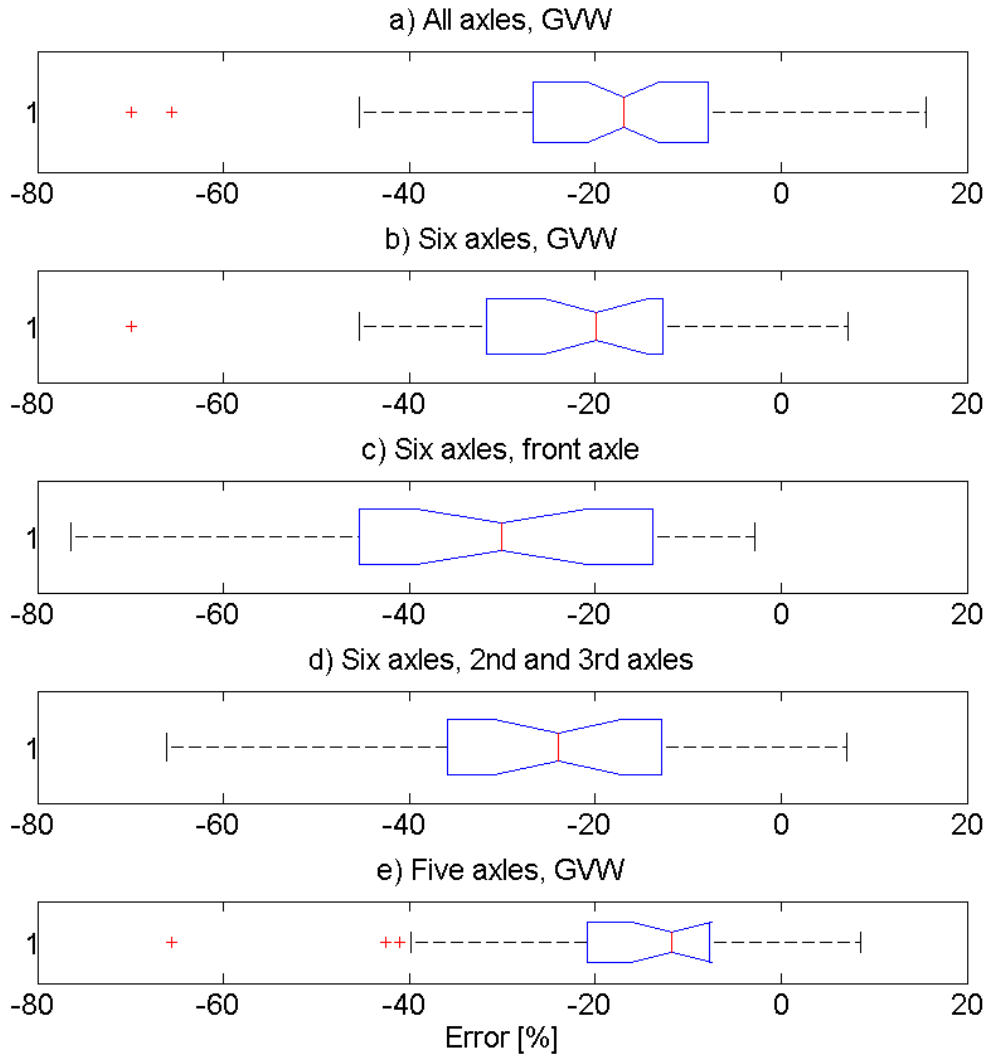


Figure 26: Errors from WIM 540032.

In figure 26, we can see that the errors are quite large and negative. The most negative median can be found at c) and is - 30 %. By look further at this box plot we can see that min-max range goes from around - 78 % to - 2 %, which is a large span that tells us that the data is very spread out. The least negative median is - 11 % and can be found at e). This box plot has the narrowest IQR, implying its values do not change that much. a), c) and d) seem to have a rather symmetric distribution, while the rest is skewed.

#### 4.4.5. WIM 540031, 27/4-2016

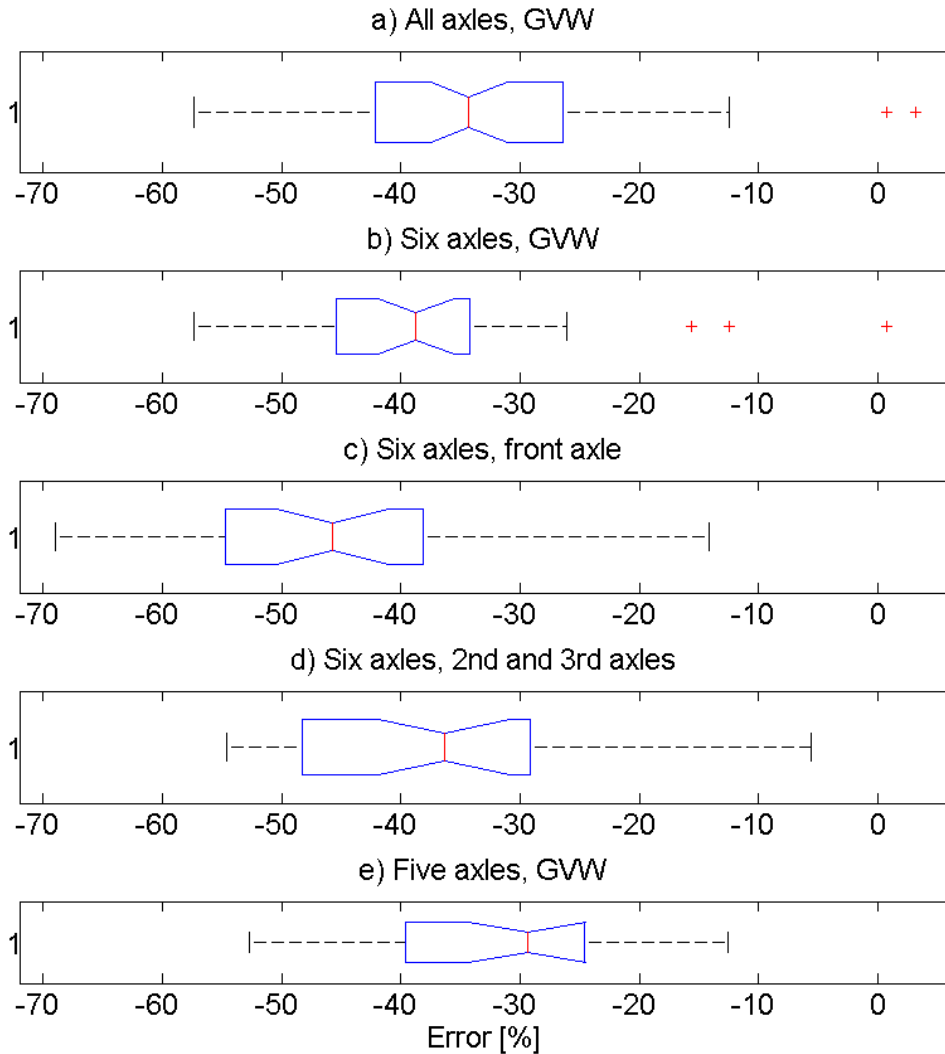


Figure 27: Errors from WIM 540031.

In figure 27, we can see that most of the medians are quite negative. c) has a median of around - 46 %, which is a lot taken into account that this is a system that should be quite accurate. The box plots are generally not the same in size, nor have the same min-max ranges. This tells us that there is a great variability between the different axle combinations that are measured. The shortest IQR range can be found in b), while the largest is in d). Box plot a) seems to have the most symmetric distribution as its median is centered in the IQR, while the other box plots are skewed to some degree.

4.4.6. WIM 540109, 27/4-2016

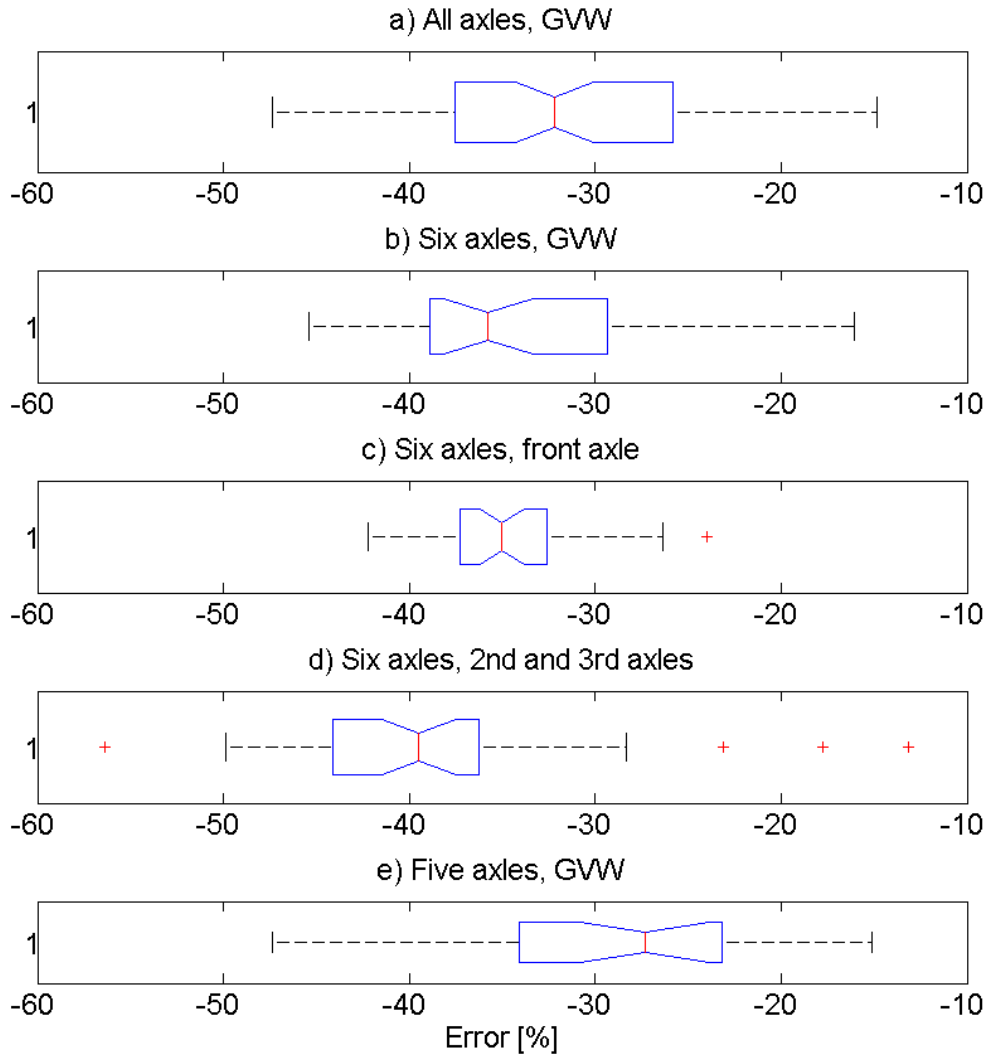


Figure 28: Errors from WIM 540109.

What can be easily seen in figure 28 is that the IQRs vary a lot between the different axle combinations. This might tell us that WIM 540109 is more sensitive to how many axles that are measured. c) has the smallest IQR and min-max range, whereas the largest IQRs and min-max ranges can be found in a) and e). The minimum-maximum ranges span from about - 15 % to - 47 %, implying a great variability. b), d) and e) seem to have skewed distributions.

## 4.5.Errors at different WIM sites when one axle combination is considered

In the following section, the errors between the WIM weights and static weights are shown in percent as a box plot. This way it is easy to assess how the errors change depending on which WIM site or axle combination is looked at. The following section shows how the different WIM sites vary when one axle combination is regarded.

### 4.5.1. All axles, GVW

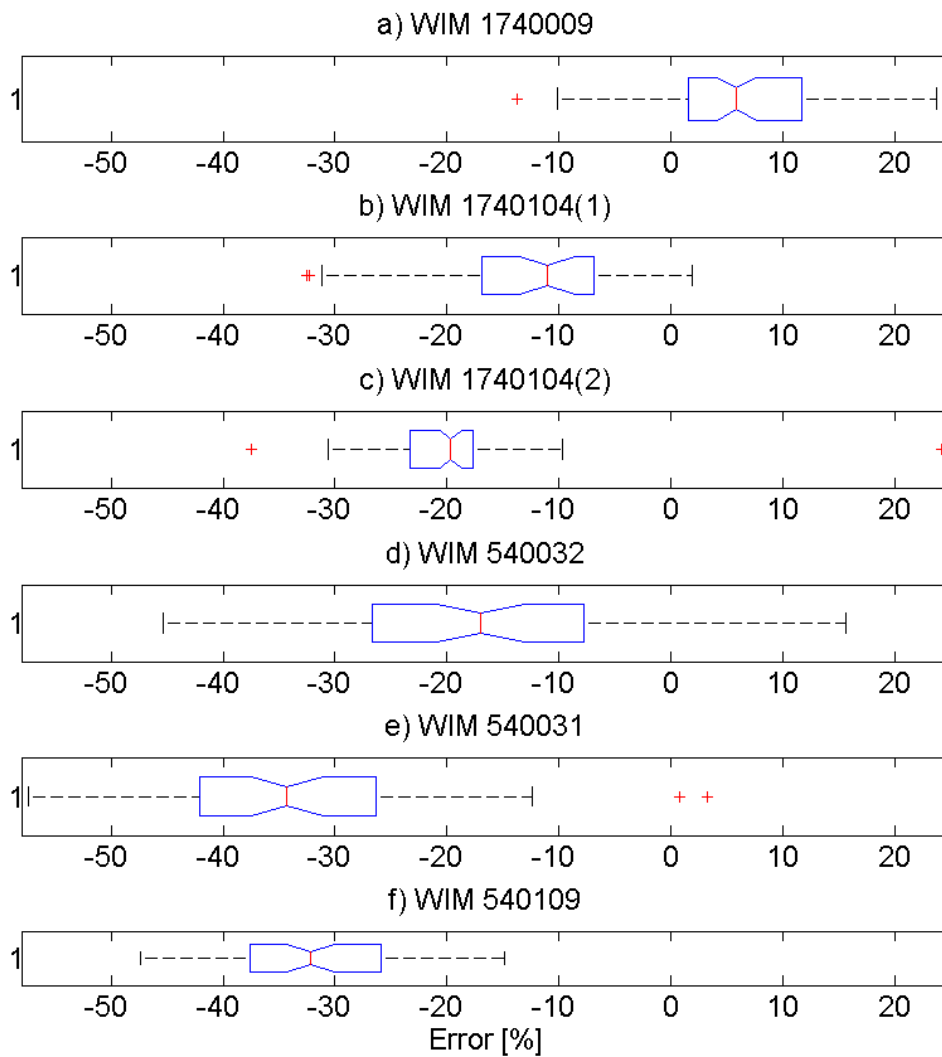


Figure 29: GVW errors of all axle vehicles from all WIM sites.

In figure 29, we can see that the only positive median can be found in a), which is about 5%. The rest span from -11% to -35%. The smallest ranges can be found in c) and that implies that this is the most precise WIM site. d) has the largest IQR and min-max range compared to

the other WIM sites, see figure 18 d). The fact that all the box plots vary a lot tells us that the accuracy for all axle vehicles changes with different WIM sites.

#### 4.5.2. Six axles, GVW

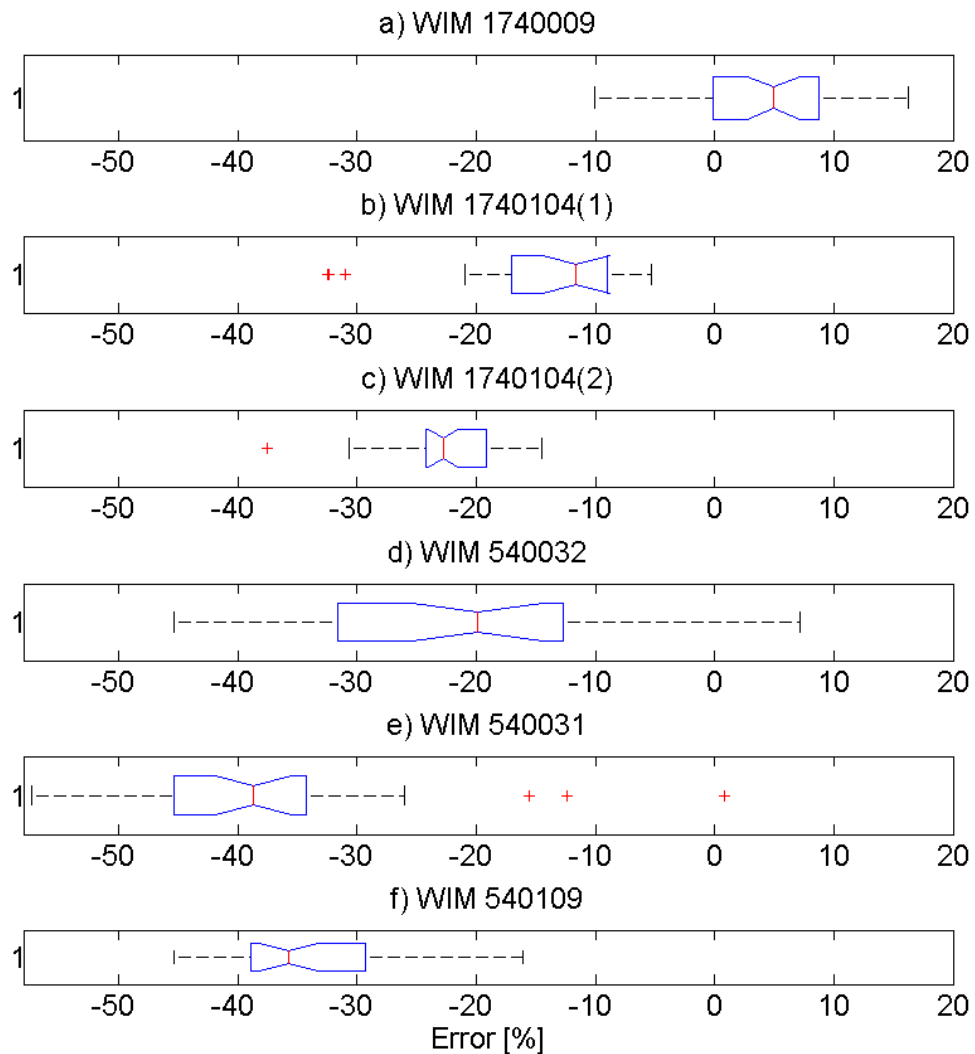


Figure 30: GVW errors of six axle vehicles from all WIM sites.

In figure 30, a) is the only box plot with a median larger than 0 %. The rest of the medians span from - 11 % to - 39 %. We can also see that there are obvious differences between the different box plots. b) and c) have quite narrow IQRs, while d) has the biggest one. This means that the accuracy of the GVW of six axle vehicles vary a lot depending on which WIM site is considered.



### 4.5.3. Six axles, front axle

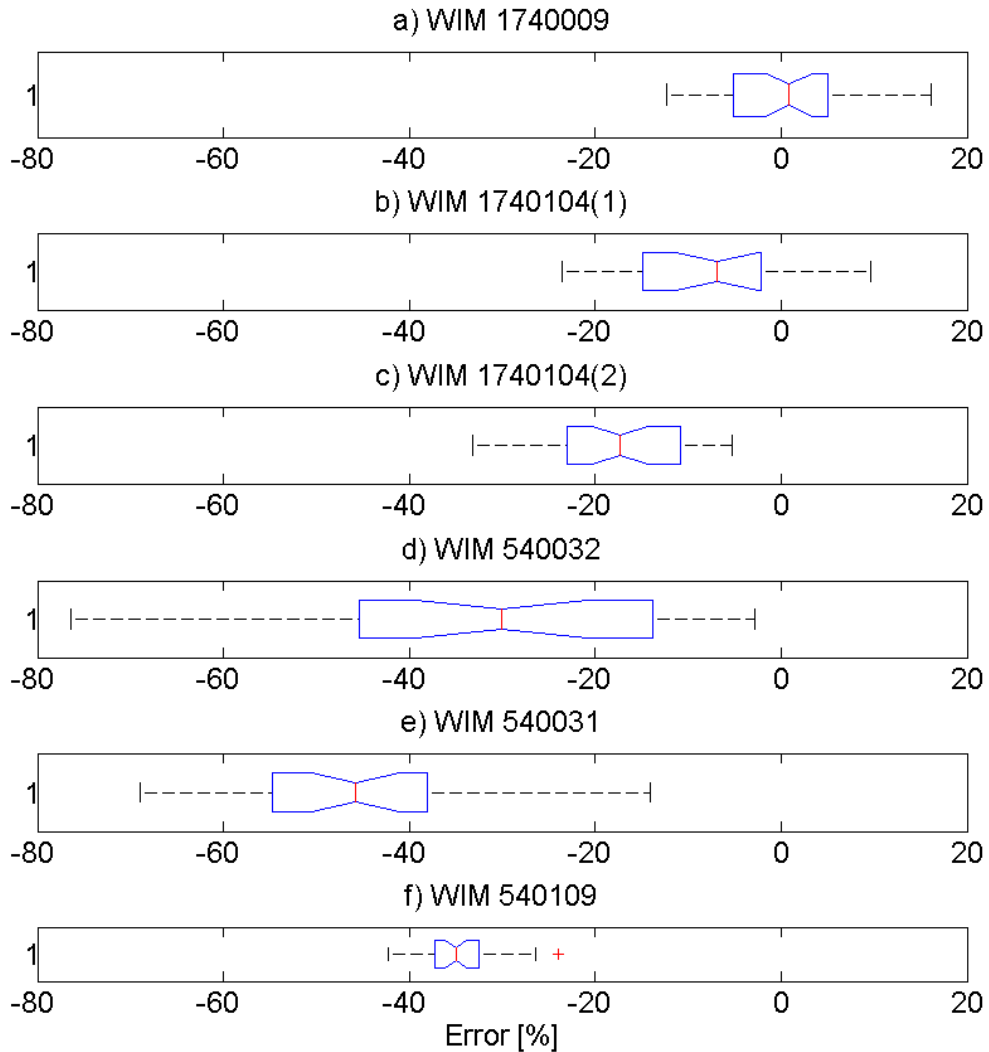


Figure 31: Front axle weight errors of six axle vehicles from all WIM sites.

In figure 30, we see the front axle weight errors of six axle vehicles. The medians vary a lot; from around  $-45\%$  in e) to  $1\%$  in a). This tells us that the measurement accuracy of the different WIM sites is quite varying. Also, a), b), c) and f) have relatively narrow min-max ranges compared to d) and e). A way of interpreting this is that they have a higher measurement precision than d) and e). This can be seen in figure 20. In general, all the WIM sites errors vary a lot when the front axle is considered.

#### 4.5.4. Six axles, 2nd and 3rd axles

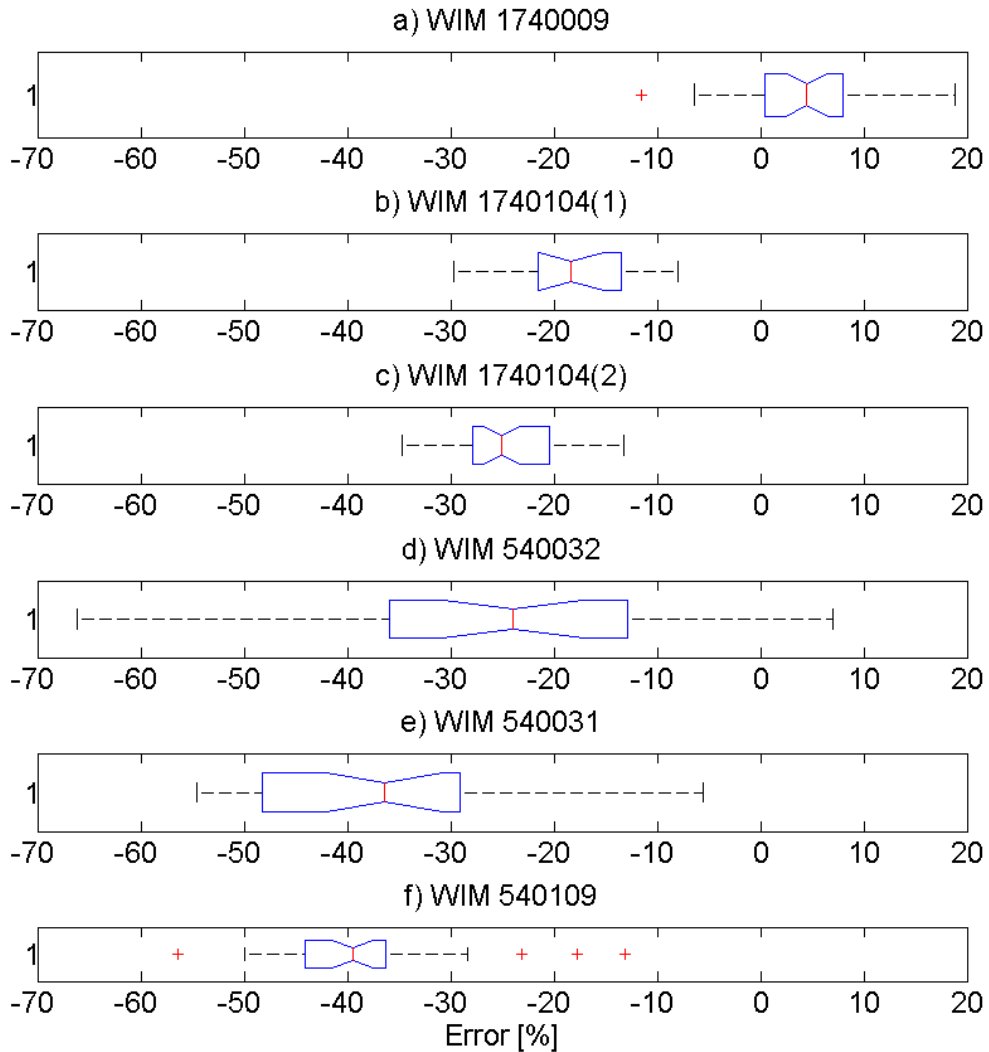


Figure 32: 2<sup>nd</sup> and 3<sup>rd</sup> axles weight errors of six axle vehicles from all WIM sites.

In figure 32, we can see that the only positive median is the one found in a). The rest are negative, spanning from around -18 % to -40 %. When looking at the min-max ranges and IQRs, this figure shows a similar tendency as the previous one, figure 31. a), b), c) and f) have quite narrow ranges, while d) and e) have rather large ranges. Another thing that can be seen is that the medians of c) and d) are more or less the same, but with different variances and symmetry.

#### 4.5.5. Five axles, GVW

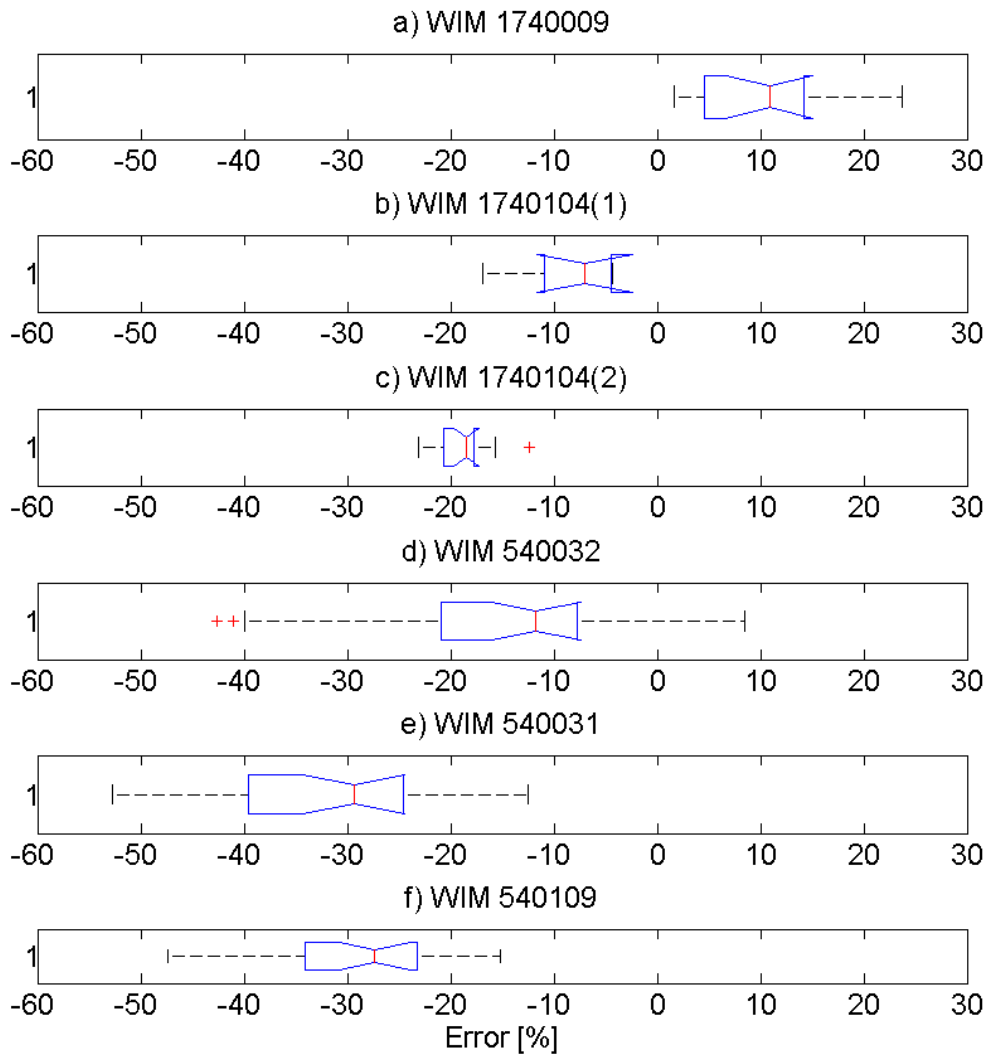


Figure 33: GVW errors of five axle vehicles from all WIM sites.

In figure 33, the GVW errors of five axle vehicles can be seen. a) has the largest positive median at around 10 %, while the most negative is  $-30$  %, found in e). c) has an unusually short ranges, while d) has the largest min-max range. We can also see that the medians of e) and f) do not differ that much.

## 4.6. Time-dependent data quality changes

In hypothesis H2 we were supposed to see if the accuracy from one WIM site changed over time. We can only check if this is the case at WIM 1740104, since this is the only site we have measured at twice. The rest had just one measurement.

### 4.6.1. All axle vehicles, WIM 1740104

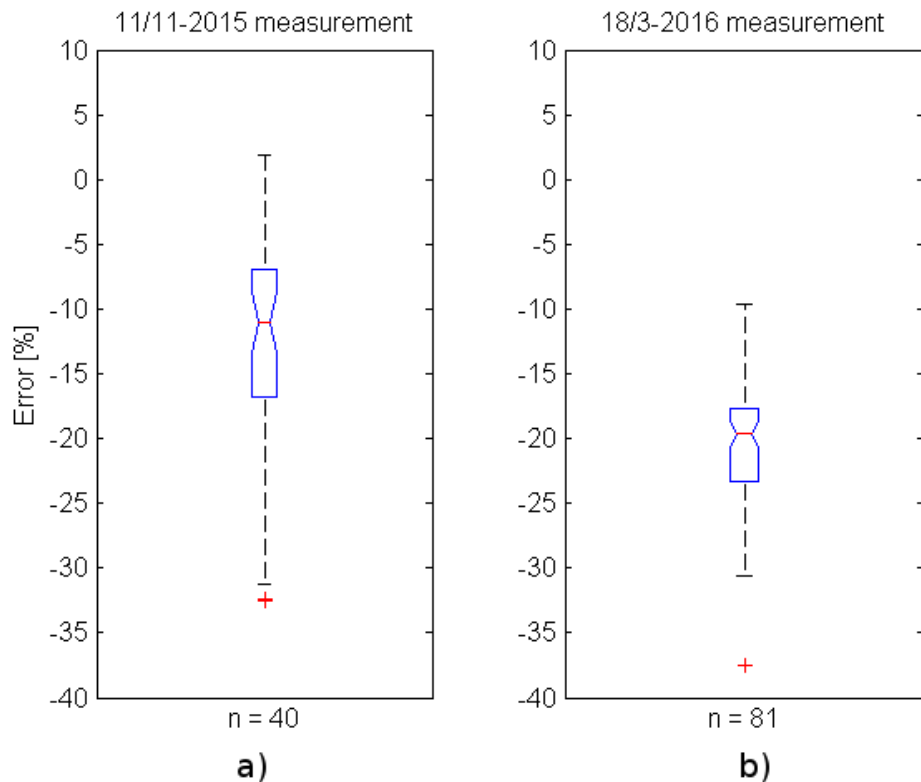


Figure 34: GVW of all axles from WIM 1740104 at two different dates with box plots showing the different measurements. The red line in the middle of the notch is the median.

In figure 34 it can be seen that a) has a wider min-max range than b). The median is a bit below -10 % and has an interquartile range from about -7 % to -16 %. b) has less variability with a median of about -19 % and an IQR from about -17 % to -23 %. This can be caused by the larger sample size. Otherwise, the min-max range is from around -9 % to -30 %. In this figure, it is easy to notice that the box plot notches (the constrictions at both sides of the median) do not overlap, and thus the medians can be roughly judged to differ significantly. In addition, it can be seen that both a) and b) have distributions that are skewed to the left, due to the medians' placement towards Q3 (the upper line on the IQR) in the box.

#### 4.6.2. Six axles, GVW

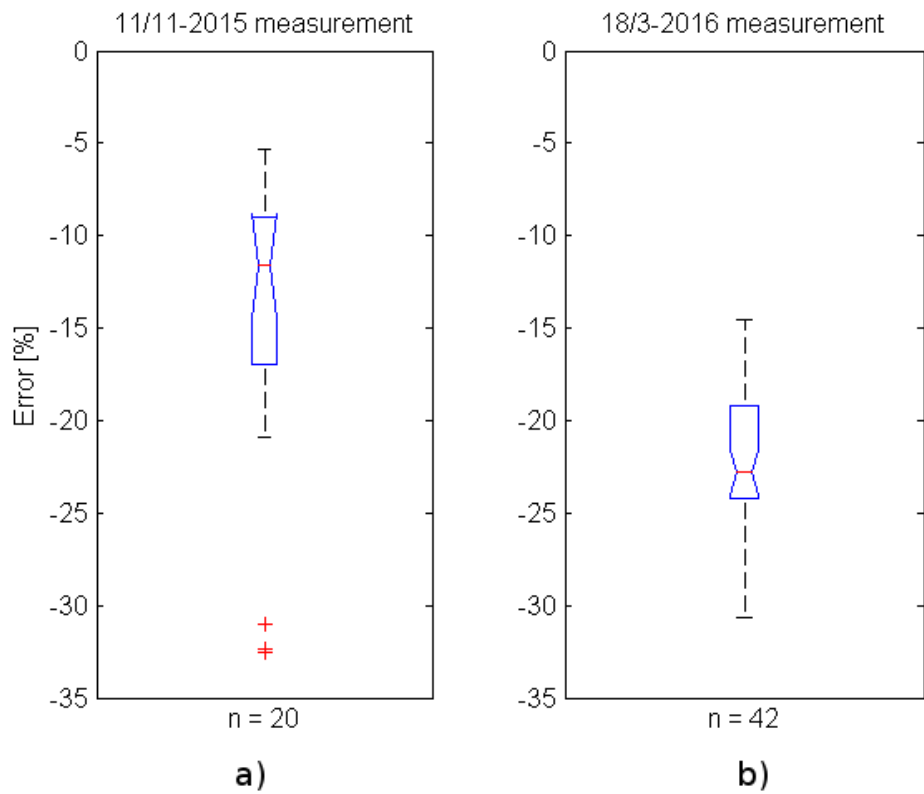


Figure 35: GVW of six axles from WIM 1740104 at two different dates.

In this figure, it can be seen that the two box plots vary mostly concerning their IQR, probably due to their different sample sizes. However, their min-max ranges is roughly of the same length their medians are quite different. While a)'s median is about -11 %, b)'s is about -23 %. When the distributions' skews are looked at, a) is left-skewed and b) right-skewed. It can also be seen that none of the box plot notches overlap and hence the medians can be said to be significantly different.

#### 4.6.3. Six axles, front axle

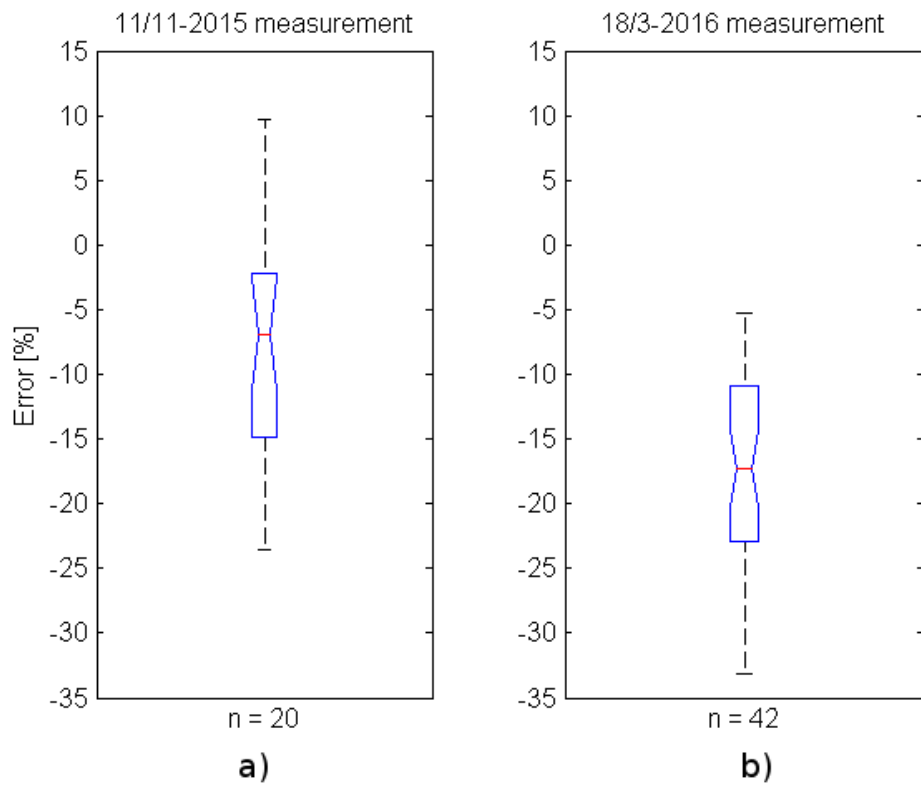


Figure 36: Front axle weight of six axles from WIM 1740104 at two different dates.

In figure 36, it can be seen that a) has a wide min-max range with a median of about -6 % and has a slight left skew, while b) has a bit shorter min-max range with a median around -16 %. The IQR is however about the same length in both a) and b). In this figure, it can be clearly seen that neither of the notches overlap, implying a statistical significance in the difference between the medians.

#### 4.6.4. Six axles, 2<sup>nd</sup> and 3<sup>rd</sup> axles

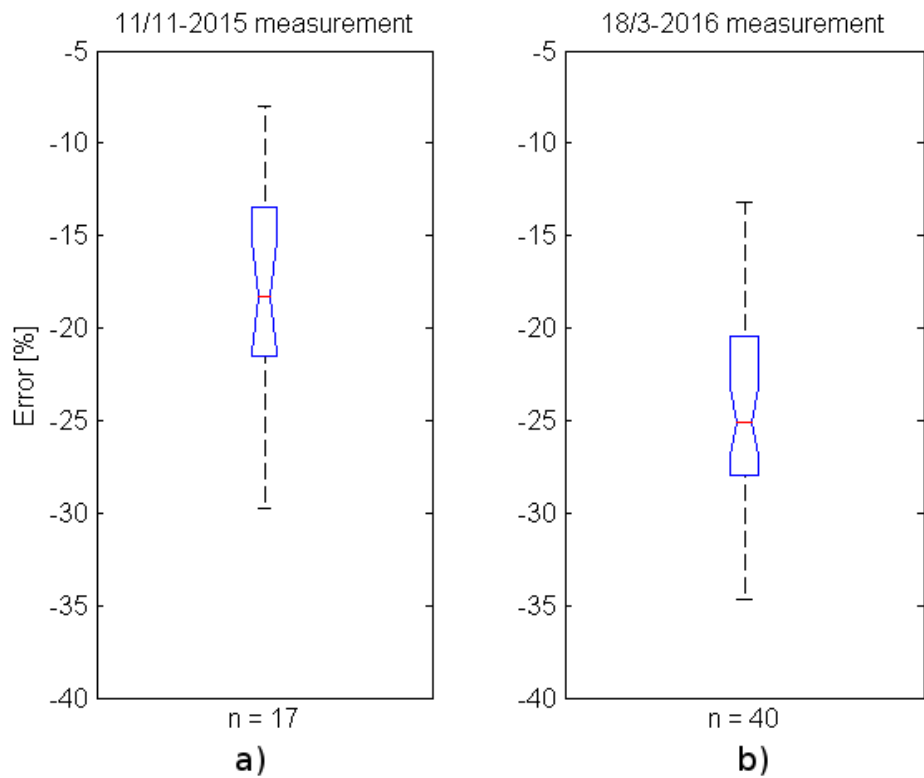


Figure 37: Weights of 2<sup>nd</sup> and 3<sup>rd</sup> axles of six axles from WIM 1740104 at two different dates

By regarding figure 37, it can be noticed that the minimum-maximum range is nearly the same in both a) and b). This can also be said about the IQR. Both distributions are skewed to the right and the median of b), -18 %, is lower than a), -25 %. The non-overlapping notches tell that the difference in medians is statistically significant.

#### 4.6.5. Five axles, GVW

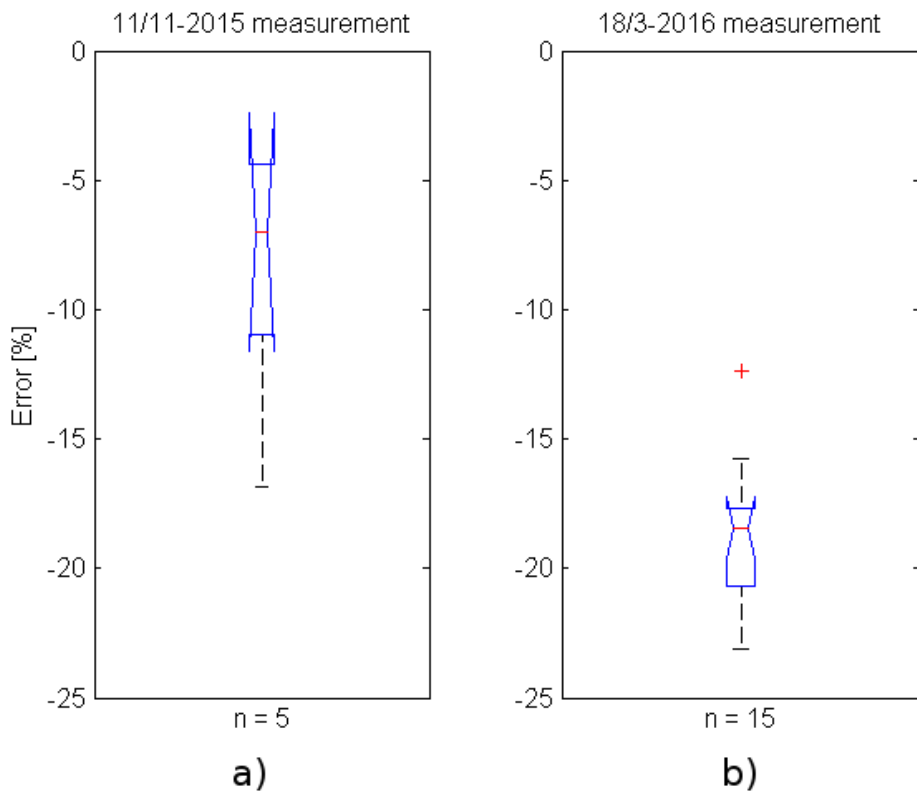


Figure 38: GVW of five axle vehicles from WIM 1740104 at two different dates

From figure 38, we can see that both samples a) and b) are quite small. A box plot requires a sample of at least five data points that is two whiskers, Q1 and Q3 marks and the median. From the notched box plots it is obvious that the notches of a) and b) do not overlap and the errors are thus significantly different. Both distributions seem relatively skewed.

#### 4.6.6. P-values and means

In table 11, we can see the p-values from the figures above. It can be seen that they are clearly smaller than the significance level of 0,05, thus rejecting the null hypothesis that there was not a difference between the two means. In figures 34 to 38 above, we could already see that the medians were statistically different by seeing if the notches overlapped or not.

Table 11: p-values for different axle combinations.  $h = 1$  means that the null hypothesis is rejected.

	<b>Axles</b>	<b>Combination</b>	<b>p-value</b>	<b>h</b>
1)	All	GVW	0,00001	1
2)	Six	GVW	0,00001	1
3)	Six	Front axle weight	0,00002	1
4)	Six	W. of 2 <sup>nd</sup> & 3 <sup>rd</sup> ax.	0,00007	1
5)	Five	GVW	0,00001	1



Table 12: Mean dynamic ( $W_d$ ) and static ( $W_s$ ) weights for different axle combinations. The difference is shown in both tonnes and percent.  $W_{fa}$  = front axle weight,  $W_{23}$  = weight of 2<sup>nd</sup> and 3<sup>rd</sup> axles.

		WIM	1740104(1)	1740104(2)			WIM	1740104(1)	1740104(2)		
	Axles	Comb.	Mean $W_d$ [t]	Mean $W_d$ [t]	Diff. [t]	Diff. [%]		Mean $W_s$ [t]	Mean $W_s$ [t]	Diff. [t]	Diff. [%]
1)	All	GVW	27,02	25,86	-1,16	-4,30		31,5	32,77	1,27	4,03
2)	Six	GVW	31,17	31,98	0,82	2,62		36,92	41,31	4,39	11,89
3)	Six	$W_{fa}$	6,62	6,04	-0,57	-8,65		7,25	7,36	0,11	1,52
4)	Six	$W_{23}$	10,88	11,39	0,51	4,72		13,28	15,12	1,84	13,86
5)	Five	GVW	25,12	20,35	-4,77	-18,98		25,01	25,12	0,11	0,44

By looking at the dynamic ( $W_d$ ) and static ( $W_s$ ) weights from both measurement dates in table 12, we can see that the mean static weights increase from WIM 1740104(1) to WIM 1740104(2) in all cases. However, the dynamic weights both increase and decrease. We can see that an increasing dynamic weight gives a correspondingly high increase in the static weight. Also, when the dynamic weight decreases, the static weight still increases, but at a more modest pace.

This can be explained by first looking at the cases where the static weight increases modestly, i.e. row 3) and 5). In those rows, the dynamic weights decrease considerably compared to the other similar weights. In other words, the static weights are almost kept constant while the dynamic weights have decreased. When looking at rows 2) and 4), in which the static weights have largely increased, the dynamic weights have almost not changed at all. This means that the dynamic weights have been kept almost constant while the static weights have increased.

What does this tell us? It tells us that some factors related to the WIM system are lowering the dynamic weight relatively to the static weight as time passes, thus increasing the error. A considerably increasing static weight seems though to retard this from happening. This is because a higher static weight consequently leads to a higher dynamic weight, but as the unknown factors still lower the dynamic weight as time passes, it remains more or less unchanged between the two dates.

Hence, the static weight difference can partly explain the increasing errors that occurred as there is a systematic error, which is an error that is proportional to the weight. This type of error could already be seen in figures 18-22. Other factors can come from parts of the weigh-in-motion systems and asphalt conditions. How much each factor contributes will not be examined in this thesis.

Further work could examine how the errors change if the mean static weight is lower than before. An assumption is that they would decrease because of the reasons stated above (less systematic error).

#### 4.7. Transferrable results from one site to other sites

In hypothesis 3 we wanted to examine whether the errors from one WIM site was related to those from other sites. We want to see if there are any interdependencies between errors from different WIM sites when one axle combination is looked at. To examine this issue, we used multiple comparison tests in MATLAB as stated previously in the method section. An interdependency would mean that the errors are *not* statistically different at a 5 % level, i.e. their 95 % confidence intervals are overlapping. When two WIM sites are interdependent, this is denoted as **X** in the following table:

Table 13: Table showing different axle combinations with p-values and an X denoting which WIM sites that are *not* statistically different. b) is WIM 1740104(1), c) is WIM 1740104(2), d) is WIM 540032, e) is WIM 540031 and f) is WIM 540109.

	N° of axles	Combination	p-value	b) + c)	b) + d)	c) + d)	d) + f)	e) + f)
1)	All	GVW	$3,41 \cdot 10^{(-86)}$		<b>X</b>	<b>X</b>		<b>X</b>
2)	Six	GVW	$6,12 \cdot 10^{(-50)}$		<b>X</b>	<b>X</b>		<b>X</b>
3)	Six	Front axle	$3,88 \cdot 10^{(-51)}$				<b>X</b>	
4)	Six	2nd + 3rd axles	$1,51 \cdot 10^{(-45)}$	<b>X</b>	<b>X</b>	<b>X</b>		<b>X</b>
5)	Five	GVW	$2,33 \cdot 10^{(-18)}$		<b>X</b>	<b>X</b>		<b>X</b>

In table 13, we can see the p-values for different combinations, which is the probability that *all* means from different WIM sites are the same. They are all extremely small, which means that the p-value is in practice zero when one axle combination is looked at. Since they are smaller than our significance level  $\alpha = 0,05$ , H3's null hypothesis can be rejected.

By looking at rows 1) and 2), we can see that they both have three intervals that overlap with the same WIM sites. Those are b) + d), c) + d) and e) + f) and are denoted by **X** in the table. The front axle in row 3) only overlaps with one different site, also seen in figure 40, while 4) overlaps with b) + c), b) + d), c) + d) and e) + f). Row 5) is equal to row 1) and 2). The graphical representation of row 2) is in figure 39 below.

A thing that should be considered is how the different axle combinations influence which intervals that are overlapping. It can be seen that the GVW in rows 1), 2) and 5) have the same overlapping intervals, whereas 3) and 4) do not completely overlap with other rows. 4) does in fact have some of the same 95 % confidence intervals as the gross vehicle weights have, except of b) + c). Therefore, it can seem like the GVW is a better parameter for errors at different WIM sites, as they correlate more, than the front axle weight and the weight of the 2<sup>nd</sup> and 3<sup>rd</sup> axles.

By looking at the X-es in the columns, it can also be seen that some WIM sites seem to correlate more than others throughout the different combinations. In the same table, we can see that b) + c), c) + d) and e) + f) are not different in four out of five axle combinations. This can tell us that those WIM sites are more correlated to each other than the rest.

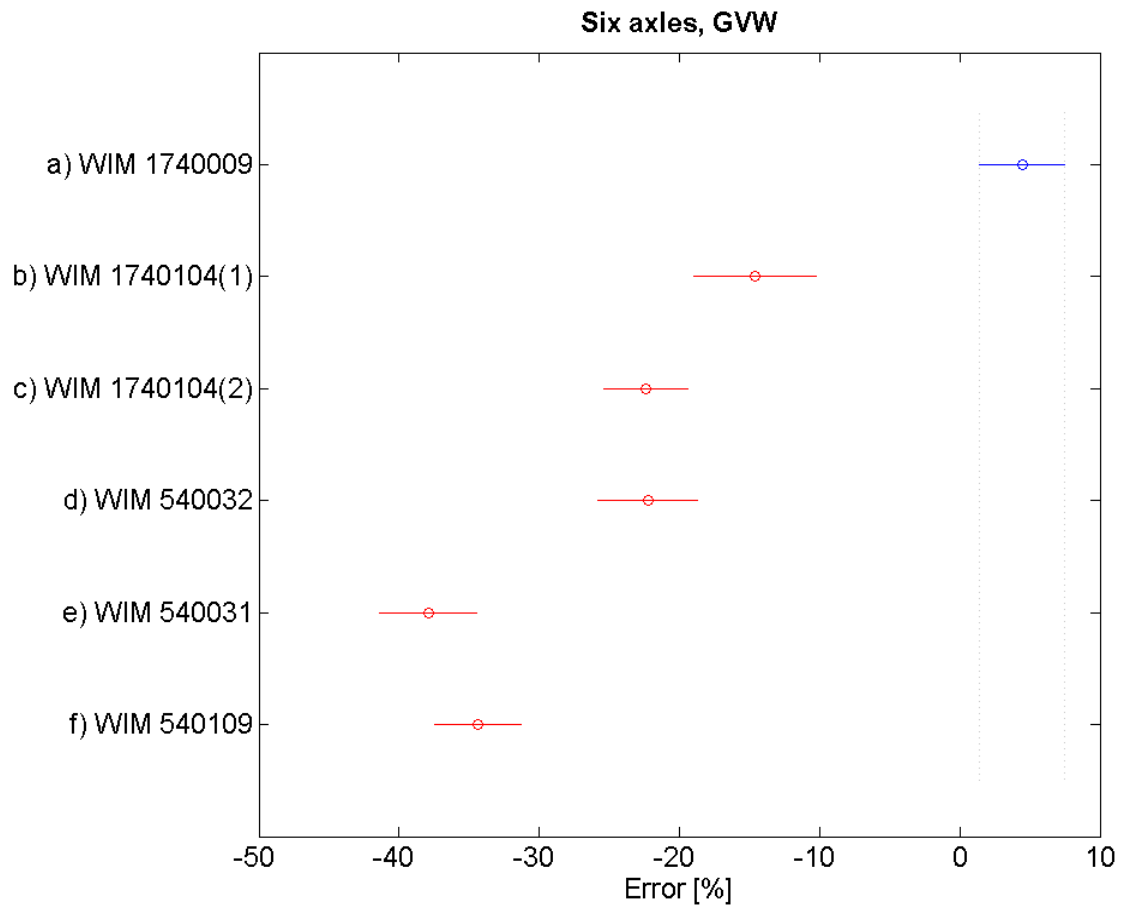
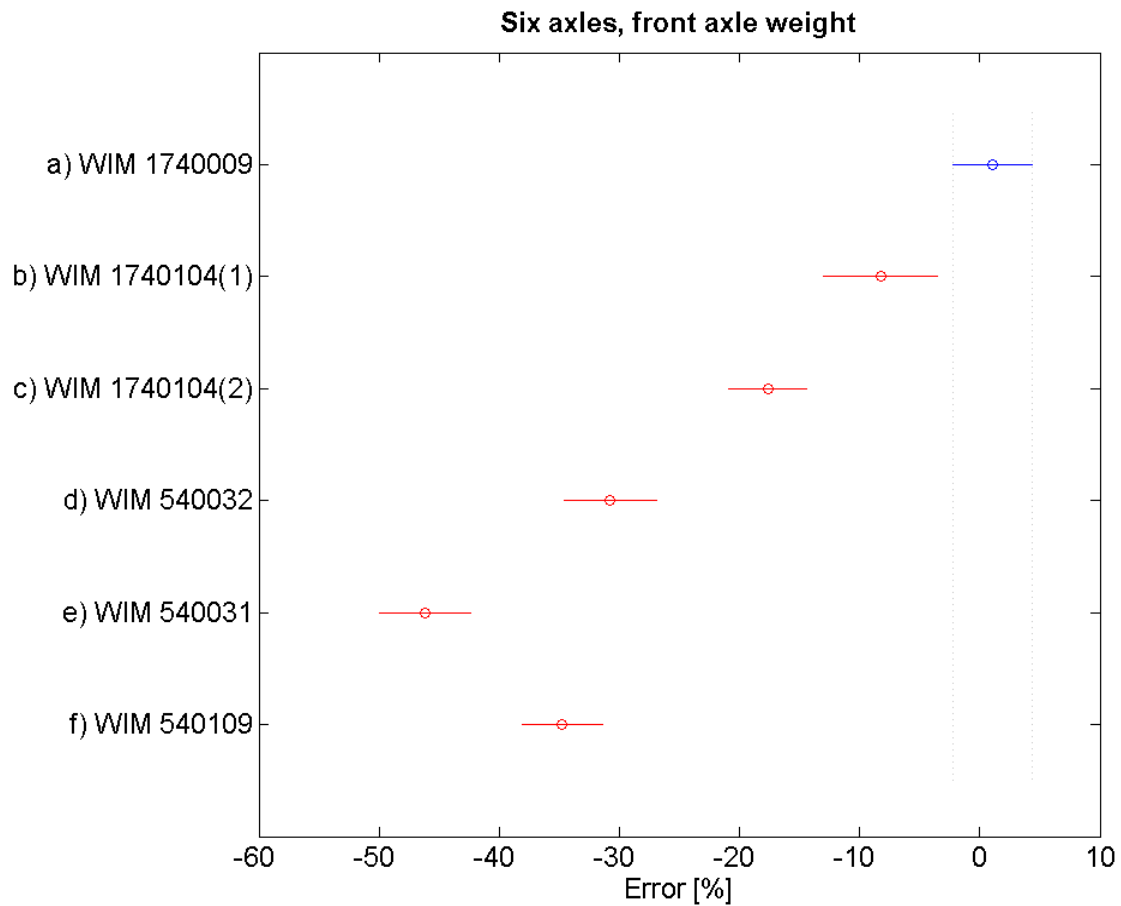


Figure 39: ANOVA plots showing 95 % confidence intervals (the horizontal line) and their medians (circle in the middle of the lines). The blue line means that a)'s confidence interval is selected, and it is not overlapping with any other WIM site.



*Figure 40: ANOVA plots showing 95 % confidence intervals (the horizontal line) and their medians (circle in the middle of the lines). The blue line means that a)'s confidence interval is selected, and it is not overlapping with any other WIM site. This can be seen by looking closely to the two vertical gray lines "hanging" from the blue line. They do not cross b)'s line and thus they are not overlapping.*

## 4.8. Calibration coefficients

Table 14: General overview of the sites and the axle combinations. A.C. = accuracy class from COST 323, SD = standard deviation.

ALL AXLES				Equation 3		Equation 4			
	WIM site	Comb.	A.C. before	Mean error [%]	SD error [%]	A.C.	Mean error [%]	SD error [%]	A.C.
1)	1740009	GVW	D+	4,40	5,51	C	2,26	5,40	C
2)	1740104(1)	GVW	D+	2,39	10,64	D	< 0,0001	10,40	D+
3)	1740104(2)	GVW	E	2,46	8,64	D+	< -0,0001	8,43	C
4)	540032	GVW	E	3,61	21,86	E	< -0,0001	21,10	E
5)	540031	GVW	E	6,14	20,97	E	< 0,0001	19,76	E
6)	540109	GVW	E	12,13	13,33	E	< 0,0001	11,89	D
SIX AXLES				Equation 3		Equation 4			
	WIM site	Comb.	A.C. before	Mean error [%]	SD error [%]	A.C.	Mean error [%]	SD error [%]	A.C.
7)	1740009	GVW	C	3,44	4,64	C	2,23	4,58	B
8)	1740104(1)	GVW	D+	2,20	10,10	D+	< -0,0001	9,88	D+
9)	1740104(2)	GVW	E	0,49	5,65	C	< -0,0001	5,62	B
10)	540032	GVW	E	3,61	21,86	E	< -0,0001	21,10	E
11)	540031	GVW	E	6,14	20,97	E	< 0,0001	19,76	E
12)	540109	GVW	E	12,13	13,33	E	< 0,0001	11,89	D
FIVE AXLES				Equation 3		Equation 4			
	WIM site	Comb.	A.C. before	Mean error [%]	SD error [%]	A.C.	Mean error [%]	SD error [%]	A.C.
13)	1740009	GVW	D	2,82	7,51	C	3,38	7,55	C
14)	1740104(1)	GVW	A	1,49	5,52	B+	< 0,0001	5,61	B+
15)	1740104(2)	GVW	D	-0,18	3,20	B+	< 0,0001	3,20	B+
16)	540032	GVW	E	5,60	22,03	E	< 0,0001	2,86	A
17)	540031	GVW	E	4,78	15,57	E	< 0,0001	14,86	E
18)	540109	GVW	E	20,77	13,55	D	< 0,0001	11,22	D+

In the methodology section, I wrote about two different methods to calibrate the dynamic weight. One was about calibration on the mean bias (equation 4) and the other was about calibration on the mean square error with a line passing through the origin (equation 3). The results are shown in table 14. As mentioned previously, this method is only suitable for GVW.

By looking at the mean error (bias) column for equation 4 in table 14, we can see that most of the mean errors are very close to zero, depending on how many decimals are used. The means that are not zero come from WIM 1740009, rows 1), 7) and 13) in the same table. This is quite interesting and by looking at figures 18 a) and 19 a), we can see why. They both seem to have a lot of statistical errors, not a systematic one as most of the others have. This means that the error will not increase when the static weights are increasing. Thus, since equation 4 calculates a calibration coefficient when there is a mean bias (systematic error), row 1), 7) and 13) will not obtain an adjusted mean error very close to zero. We can also see that all accuracy classes are as good as or better than before the corrections (A.C. before) when equation 4 is used.

By looking at figure 40 below, we can see the difference between the two types of errors: a) has a more or less symmetric distribution around a small bias and its errors are mainly statistical, while b) has a clear systematic error and the distribution is also left-skewed.

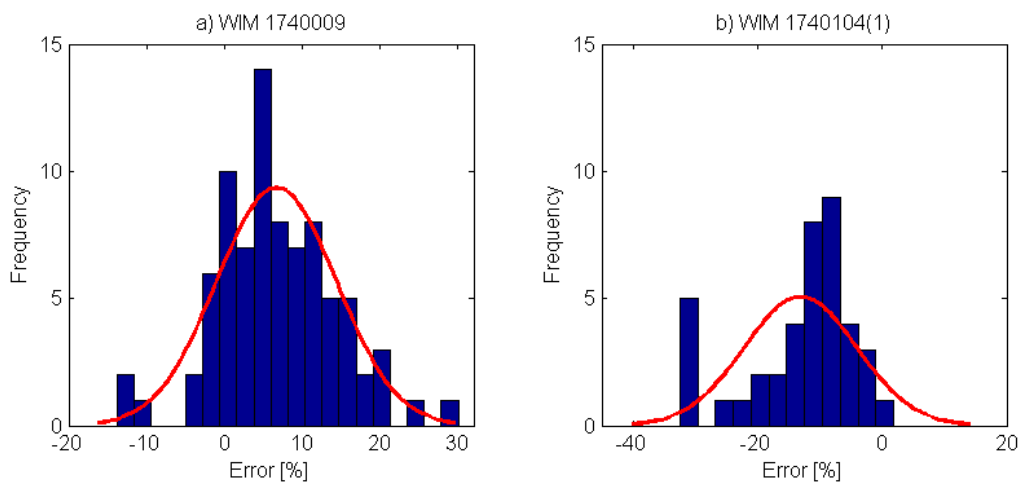


Figure 41: Histogram. Errors from gross vehicle weights of six axle vehicles. The red line denotes the normal distribution with their corresponding mean errors and standard deviations. a) has mainly statistical errors and is therefore close to a normal distribution. b) has a clear systematic error and a left-skewed distribution that cannot be fitted well to a normal distribution.

When the accuracy classes from before and after the calibration process from equation 4 are compared in table 14, we can see that 1), 3) and 6) from all axle vehicles and 7), 9) and 12) from six axle vehicles have reached a better accuracy class. Also, some rows from the five axle vehicles have improved. The rest have stayed the same. This can be explained by looking at the precision of the corresponding measurements in figures 18 to 22. Rows 1), 3), 6), 7), 9) and 12) in table 14 are all quite precise, i.e. the spread is not that big. When those dynamic weights are subsequently multiplied with their respective calibration coefficients, the results turn out to be quite ok. The axle combinations that did not achieve an accuracy class improvement have far less precise data. By looking at figure 20 e) it is very clear that these measurements have a large spread. Thus, when those dynamic weights are corrected, the spread is still large and the accuracy is actually not improved.

When we assess the results from equation 3, we can see that the mean errors are different from when equation 4 was used. They span from -0,18 % to 20,77 %. The standard deviations seem to not change that much from the previous equation. One thing that can be seen is that the accuracy classes is either the same or worse than what was achieved by equation 4, but still better or the same as the accuracy classes before any calibration. Another thing that has to be made clear is that accuracy class E is an aggregation of error confidence intervals larger than 25 %. Thus, when this class does not change from one formula to another, it is not certain whether it has about the same percentage or a quite higher one.

By looking at the calibration coefficients C in table 15, we can see how C changes with each formula. Also, as we can see, the smaller C is, the better accuracy class is achieved.

Table 15: General overview of the sites and the axle combinations with corresponding calibration coefficients (C). A.C. = accuracy class from COST 323.

<b>ALL AXLES</b>			<b>Equation 3</b>		<b>Equation 4</b>	
<b>WIM site</b>	<b>Combination</b>	<b>A.C. before</b>	<b>A.C.</b>	<b>C</b>	<b>A.C.</b>	<b>C</b>
1740009	GVW	D+	C	0,9571	C	0,9375
1740104(1)	GVW	D+	D	1,1783	D+	1,1508
1740104(2)	GVW	E	D+	1,2785	C	1,2478
540032	GVW	E	E	1,2749	E	1,2305
540031	GVW	E	E	1,5959	E	1,5036
540109	GVW	E	E	1,6418	D	1,4642
<b>SIX AXLES</b>						
<b>WIM site</b>	<b>Comb.</b>	<b>A.C. before</b>	<b>A.C.</b>	<b>C</b>	<b>A.C.</b>	<b>C</b>
1740009	GVW	C	C	0,9684	B	0,9572
1740104(1)	GVW	D+	D+	1,1969	D+	1,1711
1740104(2)	GVW	E	C	1,2948	B	1,2884
540032	GVW	E	E	1,2749	E	1,2305
540031	GVW	E	E	1,5959	E	1,5036
540109	GVW	E	E	1,6418	D	1,4642
<b>FIVE AXLES</b>						
<b>WIM site</b>	<b>Comb.</b>	<b>A.C. before</b>	<b>A.C.</b>	<b>C</b>	<b>A.C.</b>	<b>C</b>
1740009	GVW	D	C	0,901	C	0,906
1740104(1)	GVW	A	B+	1,0746	B+	1,0908
1740104(2)	GVW	D	B+	1,2274	B+	1,2296
540032	GVW	E	E	1,2577	A	1,191
540031	GVW	E	E	1,1591	E	1,4498
540109	GVW	E	D	1,6906	D+	1,3999

The reason why equation 3 gives worse results than equation 4 is due to that fact that equation 3 forces the corrected fit to go through the origin, that means a zero constant term. As seen in table 10 (p. 46), all the linear regressions have constant terms significantly different from zero. Therefore, this method will induce more errors. Equation 4 does not force the constant term to be zero and will consequently fit the previous regression lines better.

Although equation 4 is not recommended for our repeatability and reproducibility conditions cases (R1) and (R2) (p. 16), it still gives the best results for our data.

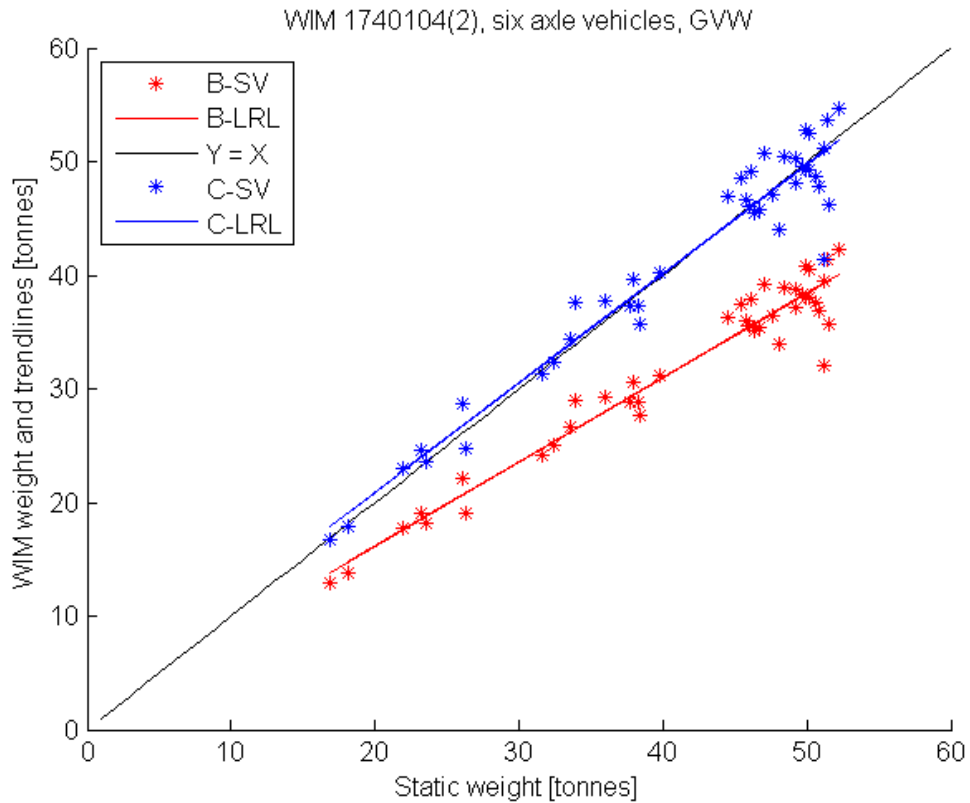


Figure 42: Row 9) in table 14. Dynamic weights from before calibration coefficients (B) and after calibration coefficient multiplication (C). By using equation 4, the accuracy class is improved from E to B. SV = single values, LRL = linear regression line.

In figure 42, we can see how equation 4 adjusts our data set. This was the equation that gave the best results. We can see that the adjusted linear regression line, which is blue, is very close to the  $y = x$  line. By regarding figure 41 below we can see the adjusted fit from the GVW from five axle vehicles at WIM 540032. The blue adjusted linear regression line is closer to the  $y = x$ , which means the average error will be smaller. But still, the accuracy class is not improved (see row 4), table 15).



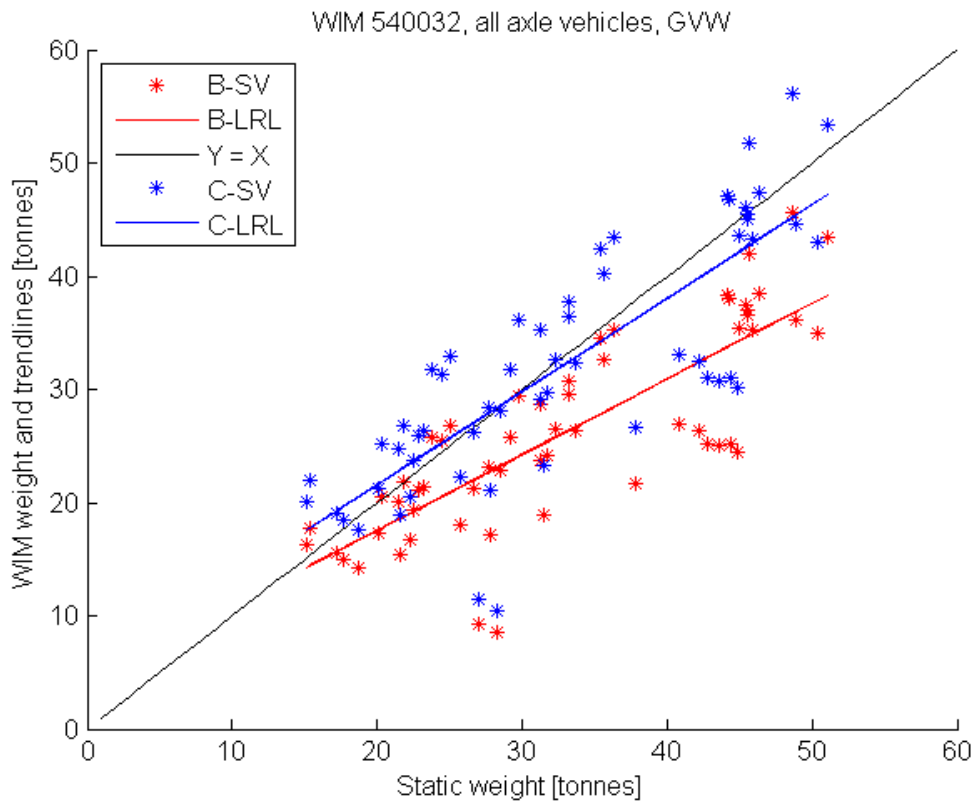


Figure 43: Row 4) in table 14. Dynamic weights from before calibration coefficients (B) and after calibration coefficient multiplication (C). By using equation 3, the accuracy class is **not** improved. SV = single values, LRL = linear regression line.

#### 4.9. Standard quality checks

In the state of the art section, Loo and Lees' (2015) data quality checks were mentioned. We were supposed to examine the mean axle distance between the second and third driven axle (abbreviated as L) on six axle tractor + semi-trailers and the mean front axle load (here abbreviated as W) of five and six axle articulated vehicles. In table 16 below I have also included the registered sample sizes from each WIM site, the parameters' calculated standard deviations (SD) to see the stability of the measurements regarding standard values. The gross vehicle weights and the proposed values from the report have been included. However, in these analyses all the WIM weights on the respective dates were analysed, not just the ones we matched with a static weight. Therefore, the sample sizes are a lot bigger and are more suitable for statistical analysis.

As a short summary of the WIM sites, 1740009 was the westmost site and 1740104(1) was the eastmost site close to Åsen during the measurement on 11/11-2015. 1740104(2) was the same site as the latter, but at a different date. 540032 was the northmost site of the section

control TEC close to Otta, while 540031 was the southmost. Site 540109 laid south of Otta.

*Table 16: Comparisons of different parameters as proposed by Loo and Lees (2015).*

<b>WIM</b>	<b>Proposed</b>	<b>1740009</b>	<b>1740104(1)</b>	<b>1740104(2)</b>	<b>540032</b>	<b>540031</b>	<b>540109</b>
n (of six axles)	-	221	156	197	151	154	307
L, 2nd and 3rd axle [m]	1,3	1,36	1,36	1,37	1,35	1,35	1,38
SD. L 2nd and 3rd axle [m]	-	0,18	0,1	0,29	0,03	0,03	0,09
W, front axle of six axles [t]	6,5-7,0	7,56	6,62	6,05	5,26	4,32	4,68
SD. front ax., six axles [t]	-	0,72	0,8	0,76	1,32	0,97	0,47
W, front axle of five axles [t]	6,5-7,0	6,84	5,8	5,13	4,5	4,01	3,59
SD. front ax., five axles [t]	-	1,13	0,91	1,06	1,64	1,38	1,3
GVW of six axles [t]	-	40,94	31,78	31,47	31,31	26,02	25,66

As we can see from table 16, all mean distances between 2nd and 3rd axle are above the proposed mean of 1,3 m. The lowest value, 1,35 m, can be found at WIM sites 540032 and 540031, and the highest value, 1,38 m, at WIM site 540109. Thus, the difference from the proposed value is 5 – 8 cm, which seems to remain somewhat stable as there are no exceptionally large averages in the table.

It would be reasonable to assume that some outliers in the data set could raise the mean axle distance. By looking at the median instead of the mean value, we can assess how much the extreme values affect the mean. This comparison is found in table 17.

*Table 17: Mean and median distance between 2<sup>nd</sup> and 3<sup>rd</sup> axles on six axle vehicles.*

<b>WIM</b>	<b>Proposed</b>	<b>1740009</b>	<b>1740104(1)</b>	<b>1740104(2)</b>	<b>540032</b>	<b>540031</b>	<b>540109</b>
Mean distance [m]	1,3	1,36	1,36	1,37	1,35	1,35	1,38
Median distance [m]	-	1,35	1,36	1,36	1,36	1,35	1,38

As we can see from table 17, the median distances is more or less the same as the mean distances. Only WIM 1740009 and WIM 1740104(2) have a change of -0,01 m from the mean to the median. Thus, the median values are only slightly closer to the proposed 1,3 m. Another thing to notice is that the only changes in this table are at those sites at which the standard deviations of the axle distances are relatively big (see table 16).

By looking at the standard deviations of the axle distances, we can see that most sites have a small value, indicating a narrow distribution. However, the standard deviations of WIM 1740009 and WIM 1740104(2) have clearly the largest values compared to the other sites. This tells us that those two distributions are probably not normally distributed, as this would lead to unlikely small or negative values for the axle distances. Another observation supporting this assumption is that medians and means should be equal if they were normally distributed.

By regarding the data set from WIM 1740009, three outliers are found: 3,34 m, 2,56 m and 2,56 m. When those are removed, a mean axle distance of 1,32 m and standard deviation of 0,02 m is found. The same can be performed on the data from WIM 1740104(2). There an outlier of 5,42 m is found, which is relatively large. By removing this value, we end up with a mean of 1,35 m and a standard deviation of 0,03 m. Thus, when the outliers are removed, the values from the two WIM sites are a lot more similar to those from the other sites.

When the average weights of the front axles are examined in table 16, the numbers vary a lot. The highest value for six axle vehicles is found at WIM 1740009 with an average of 7,56 tonnes, while the lowest is at WIM 540109 with an average of 4,68 tonnes. Only WIM 1740104(1) falls within the limits of 6,5-7,0 tonnes with a weight of 6,62 tonnes. When the front axle loads from five axle vehicles are examined, we can see that only WIM 1740009 satisfy the limits with a front axle load of 6,84 tonnes.

When we consider the time-dependent changes of 1740104, we can see that the front axle loads of both five and six axle vehicles are reduced from 1740104(1) to 1740104(2). This leads us back to the results from hypothesis 2, to which I commented that if the mean of the static weights increases, the errors will also increase. As we saw in the same section, the mean static weight is in fact higher at 1740104(2) than at 1740104(1). Consequently, the error must be larger at 1740104(2) and thus the front axle weight must follow likewise. From table 10, row 20) and 21), we saw that there was a systematic error causing a too low WIM weight and therefore the error must be more negative than before.

As a further comment to the results from table 16, the accuracy classes (found in table 10) of the front axle loads can be brought in. By looking at the front axle loads from six axle vehicles, it can be seen that WIM 1740009 reaches accuracy class B (row 19), the 3<sup>rd</sup> best class possible, while WIM 1740104(1) reaches accuracy class C and WIM 1740104(2) accuracy class D. The three last WIM sites, 540032, 540031 and 540109, also fulfill accuracy class E, which is the worst one. Here it seems like a lower accuracy class gives a lower front axle load and a lower gross vehicle weight. By having a look at figure 22, it tells us that the WIM weights from WIM 540032, 540031 and 540109 in general are too low compared to the static weight, thus gives a lower front axle load.

It is reasonable that average distances between the 2nd and 3rd axle don't vary that much. The reason for this is that those kind of measurements are independent of the axle loads passing the piezoelectric sensors, as they just measure at which times the 2nd and 3rd axles pass the sensors and thus calculate the axle distance since the sensor spacing is known. This independency can be shown by comparing the axle distances with the gross vehicle weights (GVW). They do not seem to be correlated at all, as the GVWs can go from 40,94 tonnes to 25,66 tonnes and almost do not affect the axle distance at all.



## 4. Discussion

In this master's thesis, I had three hypotheses and three needs for WIM data mentioned in the introduction. Hypothesis H1 was if there was a difference between the WIM weights and the static weights. All the null hypotheses were rejected except for one that was the front axle weight of six axle vehicles at WIM 1740009. This combination has the lowest mean error when the dynamic weights are compared to the static weights. We have also seen that most of the sites have a systematic error, while a very few have statistical errors.

Consequently, every WIM site varies a lot in terms of accuracy and precision. As a direct cause of that, the accuracy classes have in general not been very good. The reasons for that are complex and there is no simple explanation for why the different sites are so unlike. Other factors such as road surface integrity, piezoelectric cable depths, temperature, road composition, road wear, weather conditions and road geometry can also explain the poor results. Moreover, the accuracy will also depend on if there is a systematic or random error. When the vehicle loads are high and there is a random error, the accuracy will stay quite good. The reason for this is that random errors at high loads will only result in small percentage errors, whereas if the error were systematic, the weight would be proportional to the error and the accuracy would worsen.

The second hypothesis H2 was about if there was a time-dependent difference between the WIM weight and the static weights. We can indeed see from both the notched box plots and the p-values that there was a significant difference, which rejected the null hypothesis. However, as I have shown in the results part, different mean static weights partly influence this change. Since we are not weighing random vehicles when we collect our data, our samples cannot be said to be representative. Because of that the mean static weight will change at different data acquisitions and thus the error will also change due to a systematic error. It is therefore not unambiguous that only time affects the errors, but also other factors like increased road wear and errors within the weigh-in-motion systems. This also means that reproducing these results, as well as the results from H1 and H3, can be a bit challenging as the accuracy changes over time. Obtaining representative vehicle samples could however improve the data quality.

The third and final hypothesis H3 was if the difference between the WIM weights and the static weights was not the same at different WIM sites. The p-values indicated a very small probability that the differences were the same, or put in another way, that all the WIM sites had interdependencies. The null hypothesis was consequently rejected. Through analysis of variance tools, we have though seen that some WIM sites and axle combinations seem to correlate more than others do. This is the case when the gross vehicle weight is examined, which other reports have said to be more reliable than other single- or multiple-axle combinations. By looking at figures 23-28 we can see that the errors vary a lot depending on which combination is looked at. This supports the allegation that all axle combinations are very unlike.

In the introduction, one need for WIM data was to pre-screen possible overweight vehicles and have them weighed at a traffic station nearby. According to COST 323, accuracy class B is needed for pre-screening of overweight vehicles. That class or better is found in table 10, row 19) and in row 26). The former is the front axle of six axle vehicles and cannot be used for GVW estimation unless the load distribution is already known. The latter is the GVW of five axle vehicles and has only a sample size of  $n = 5$ , which makes it too uncertain. When the weights are adjusted with calibration coefficients, even more rows satisfy class B or better. However, the adjusted data is not valid for pre-screening because it is adjusted *after* we have collected the data and not in real time. Consequently, none of the data from our WIM sites can be used for pre-screening of possible overweight vehicles.

The second need for WIM data was to acquire better statistics over vehicle composition concerning the design of new roads and estimating road deterioration. According to COST 323, class B, C and D+ or better can be used for this purpose, classes which occur frequently in our data. Some examples are row 1), 7) and 19) in table 10. When the data is adjusted with calibration coefficients, we can see that even more rows obtain a better accuracy class. Consequently, certain WIM sites with certain axle combinations can be used for obtaining better statistics over the vehicle composition, assuming that the errors do not increase over time.

The third and last need is to acquire weight data from roads with limited allowed axle loads, such as bridges, to see if the regulations are being complied. The best suited accuracy class for this purpose is class A, which is used for enforcement of legal weight limits. Only row 26) in figure 12 has class A, but its sample size was very small ( $n = 5$ ) and is therefore highly uncertain for further use. After the adjustment of the dynamic weights by using calculated calibration coefficients, only row 16) in table 12 obtains class A. This row contains the GVW of five axle vehicles at WIM 540032. The row that had accuracy class A before the calibration coefficient multiplication, now has class B+. Thus, our WIM data cannot in general be used for axle load enforcement.

From the standard quality checks report by Loo and Lees, we have seen that the mean axle distance between the 2<sup>nd</sup> and 3<sup>rd</sup> driven axle was quite stable, but not so accurate. This means that the WIM sites may have a deficiency that increases the mean distance. We also saw that the standard deviations were quite different from each other, implying that some of the distributions were normally distributed, while the others were not. The latter was caused by some outliers.

Furthermore, we can see that a decreasing gross vehicle weight leads to a decreasing front axle weight. This is natural, because if the whole vehicle in average weighs less, it puts less pressure onto the front axle. It has to be said that this is not necessarily caused by vehicles actually weighing that little, but that the poor accuracy leads to higher systematic errors and thus a lower dynamic weight. The last three WIM sites in table 16 have the lowest GVW and also the worst accuracy classes. Thus, our data can not satisfy the standard parameters.

Throughout this thesis, we have also seen that our WIM sites did not always entirely suit the geometric and asphalt criteria proposed by COST 323. This is likely to affect our results and can therefore partly explain why the accuracy changes so much from one WIM site to another. Furthermore, it is also not certain how different shapes of the piezoelectric cables influence the results. It would certainly be interesting to see how the data would be if all the sites were identical in terms of road geometry and the system components.

Further work could take a closer look at just a few WIM sites and perform multiple data acquisitions to see how their accuracies change over a longer period, let us say a few months. If data were collected once a week during eight weeks at several sites, one could investigate how fast the accuracy changes, if it actually does, for example recording the time needed to conclude that the difference is significant and also examine how fast the different sites change compared to each other. It would also be possible to look at how single factors affect the data, the mean static weight as the most relevant factor, or as mentioned previously, temperature and climate conditions. Measuring road wear could also be examined. This would help to clarify how much each factor contributes and thus determine the most important sources of error in the WIM data.





## 5. Conclusion

In this thesis, I have looked at how data from weigh-in-motion systems can be used for road planning and legal purposes by using methodology from WIM standards. I have also assessed the data quality and explained why the data is not always very accurate.

We have researched how well the dynamic weights correspond to the static weights, how the accuracy changes over time and if the different WIM sites show similar properties concerning varying axle combinations.

Our main findings is that generally there is a large discrepancy between the dynamic and static weights, mainly due to systematic errors. The data is though accurate enough to be used for road planning purposes, but not for legal purposes, like weight restriction enforcement. Moreover, we have seen that unrepresentative vehicle samples during the static weight acquisition influence the errors. Many other factors are also thought to play a role in this, but their contribution has not been quantified here. We have also seen that the GVW seems to have errors that remain more constant than other axle combinations, like the front axle load or 2<sup>nd</sup> and 3<sup>rd</sup> axle. Also, using calibration coefficients have helped improve the accuracy classes.

Further work could try to isolate certain factors related to WIM and examine how they affect the accuracy by doing more frequent data acquisitions. It could also be investigated how a representative sample of vehicles could be achieved when there are large and small sample sizes. This could consequently improve the statistics of vehicle composition on the road network.



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## Attachments

Attachment 1: Oppgavebeskrivelse.....	87
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Attachment 3: Graphical ANOVA.....	94

### Electronic attachments:

- MATLAB scripts
- Weight sheets
- WIM data





## **MASTEROPPGAVE**

(TBA4945 Transport, masteroppgave)

VÅREN 2016  
for  
**Timothy Pedersen**

### A Time-Dependent and Parametrical Assessment of Weigh-in-Motion Data

#### **BAKGRUNN**

Statens vegvesen har de siste årene etablert en del WIM-punkt (Weigh-In-Motion) på veger rundt om i Norge. Vektdata fra slike punkter er etterspurt i forbindelse med effektiv kontroll av tunge kjøretøy, nedbrytning/slitasje på vegnettet, dimensjonering av nye veger, aksellastrestruksjoner på bruer og trafikkstatistikk generelt.

Utfordringen med WIM data er å få et system som sikrer kvalitet på data over tid. Erfaringen med de punktene vi har etablert er at data har bra kvalitet i en periode etter kalibrering av punktet, men at kvaliteten reduseres over tid. Det er dyrt og tidkrevende å kalibrere punktene, og samtidig er det en utfordring å finne hvilke faktorer som påvirker dette kvaliteten. Det vil si når og hvordan kvaliteten endres over tid og når det må recalibreres.

I Norge har vi en spesiell løsning for ATK (automatisk trafikkontroll), ved at sensorene som benyttes til å registrere hastigheten ved fotoboksene, er samme type sensorer som benyttes av mange WIM- systemer. Sensorene som brukes er piezoelektriske kabler eller trykkfølsomme kabler. Det betyr at vi får et «vektsignal», men programvaren som benyttes er ikke spesielt utviklet for å tolke dette signalet siden det er hastigheten som er i fokus på ATK-punktene. Punktene er heller ikke kalibrert, og de har ikke temperatursensorer for å korrigere vektdata. Men det registreres en vekt for hver aksling og totalt for kjøretøyet.

Vi har mellom 250 og 300 ATK-punkt i Norge. Dersom det er mulig å utnytte vektdata fra disse vil vi kunne få en stor mengde data uten kostnader med å etablere egne WIM-punkt. I masteroppgaven skal kandidaten se nærmere på denne muligheten, og vurdere om disse vektdataene har en kvalitet som slik at de kan benyttes i stedet for å etablere spesielle WIM-punkt.

#### **OPPGAVE**

##### **Målsetting og hensikt**

Målsettingen med oppgaven er å vurdere om vektdata fra ATK-punkt kan anvendes, og i tilfelle hvordan. Hensikten med å anvende denne type data er at vi i Norge har en mengde ATK-punkt, og det vil være store besparelser ved å utnytte eksisterende infrastruktur i stedet for å anlegge spesielle WIM-punkt.



## **Beskrivelse av oppgaven**

Oppgaven går ut på å undersøke et eller flere ATK-punkt for å se hvor nøyaktige WIM-dataene er, og om eventuelle avvik er systematiske slik at de kan beskrives matematisk. Her skal kandidaten samle inn og sammenstille vektdata fra ATK-punkt og en statisk vekt på en kontrollstasjon i nærheten. Data fra kontrollstasjonen antas å være fasit, og ut fra dette skal kvaliteten på WIM-data vurderes.

Kandidaten skal om mulig følge opp et eller flere ATK-punkt over tid, og studere om kvaliteten på vektdata forandres.

Kandidaten skal også analysere tilgjengelige data med tanke på å forklare hvilke faktorer som påvirker datakvaliteten, samt foreslå metoder som kan forbedre nøyaktigheten på eksisterende datasett. I dette arbeidet skal kandidaten vurdere om det finnes noen parametere som skal være innenfor visse grenser, og som dermed kan benyttes for å vurdere datakvaliteten. Videre skal kandidaten også vurdere om resultatene er generelle og kan overføres til andre WIM-punkt.

Kandidaten skal avslutningsvis diskutere bruksområder for vektdata fra ATK basert på de funn som er gjort i oppgaven.

## GENERELT

Opgaveteksten er ment som en ramme for kandidatens arbeid. Justeringer vil kunne skje underveis, når en ser hvordan arbeidet går. Eventuelle justeringer må skje i samråd med faglærer ved instituttet.

Ved bedømmelsen legges det vekt på grundighet i bearbeidningen og selvstendigheten i vurderinger og konklusjoner, samt at framstillingen er velredigert, klar, entydig og ryddig uten å være unødig voluminøs.

Besvarelsen skal inneholde

- standard rapportforside (automatisk fra DAIM, <http://daim.idi.ntnu.no/>)
- tittelside med ekstrakt og stikkord (mal finnes på siden <http://www.ntnu.no/bat/skjemabank>)
- sammendrag på norsk og engelsk (studenter som skriver sin masteroppgave på et ikke-skandinavisk språk og som ikke behersker et skandinavisk språk, trenger ikke å skrive sammendrag av masteroppgaven på norsk)
- hovedteksten
- oppgaveteksten (denne teksten signert av faglærer) legges ved som Vedlegg 1.

Besvarelsen kan evt. utformes som en vitenskapelig artikkel for internasjonal publisering. Besvarelsen inneholder da de samme punktene som beskrevet over, men der hovedteksten omfatter en vitenskapelig artikkel og en prosessrapport.

Instituttets råd og retningslinjer for rapportskrivning ved prosjektarbeid og masteroppgave befinner seg på <http://www.ntnu.no/bat/studier/oppgaver>.

### Hva skal innleveres?

Rutiner knyttet til innlevering av masteroppgaven er nærmere beskrevet på <http://daim.idi.ntnu.no/>. Trykking av masteroppgaven bestilles via DAIM direkte til Skipnes Trykkeri som leverer den trykte oppgaven til instituttkontoret 2-4 dager senere. Instituttet betaler for 3 eksemplarer, hvorav instituttet beholder 2 eksemplarer. Ekstra eksemplarer må bekostes av kandidaten/ ekstern samarbeidspartner.

Masteroppgaven regnes ikke som ferdig levert før kandidaten har levert innleveringsskjemaet (fra DAIM) hvor både Ark-Bibl i SBI og Fellestjenester (Byggsikring) i Sentralbygg II har signert på skjemaet. Innleveringsskjema med de aktuelle signaturene underskrives av instituttkontoret før skjemaet leveres Fakultetskontoret.

Dokumentasjon som med instituttets støtte er samlet inn under arbeidet med oppgaven skal leveres inn sammen med besvarelsen.

Besvarelsen er etter gjeldende reglement NTNUs eiendom. Eventuell benyttelse av materialet kan bare skje etter godkjennelse fra NTNU (og ekstern samarbeidspartner der dette er aktuelt). Instituttet har rett til å bruke resultatene av arbeidet til undervisnings- og forskningsformål som om det var utført av en ansatt. Ved bruk ut over dette, som utgivelse og annen økonomisk utnyttelse, må det inngås særskilt avtale mellom NTNU og kandidaten.

**(Evt) Avtaler om ekstern veiledning, gjennomføring utenfor NTNU, økonomisk støtte m.v.**  
Beskrives her når dette er aktuelt. Se <http://www.ntnu.no/bat/skjemabank> for avtaleskjema.

**Helse, miljø og sikkerhet (HMS):**

NTNU legger stor vekt på sikkerheten til den enkelte arbeidstaker og student. Den enkeltes sikkerhet skal komme i første rekke og ingen skal ta unødige sjanser for å få gjennomført arbeidet. Studenten skal derfor ved uttak av masteroppgaven få utdelt brosjyren "Helse, miljø og sikkerhet ved feltarbeid m.m. ved NTNU".

Dersom studenten i arbeidet med masteroppgaven skal delta i feltarbeid, tokt, befarings, feltkurs eller ekskursjoner, skal studenten sette seg inn i "Retningslinje ved feltarbeid m.m.". Dersom studenten i arbeidet med oppgaven skal delta i laboratorie- eller verkstedarbeid skal studenten sette seg inn i og følge reglene i "Laboratorie- og verkstedhåndbok". Disse dokumentene finnes på fakultetets HMS-sider på nettet, se <http://www.ntnu.no/ivt/adm/hms/>. Alle studenter som skal gjennomføre laboratoriearbeid i forbindelse med prosjekt- og masteroppgave skal gjennomføre et web-basert TRAINOR HMS-kurs. Påmelding på kurset skjer til [sonja.hammer@ntnu.no](mailto:sonja.hammer@ntnu.no)

Studenter har ikke full forsikringsdekning gjennom sitt forhold til NTNU. Dersom en student ønsker samme forsikringsdekning som tilsatte ved universitetet, anbefales det at han/hun tegner reiseforsikring og personskadeforsikring. Mer om forsikringsordninger for studenter finnes under samme lenke som ovenfor.

**Oppstart og innleveringsfrist:**

Oppstart og innleveringsfrist er i henhold til informasjon i DAIM.

**Faglærer ved instituttet:** Torbjørn Haugen

**Veileder(eller kontaktperson) hos ekstern samarbeidspartner:** Jorunn R. Levy

Institutt for bygg, anlegg og transport, NTNU

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Underskrift

  
Faglærer

**ny\_alle\_tot\_error.m**

(Calculates the errors and linear regressions from WIM 540032, 540031 and 540109)

```

clear all;
close all;
clc;
tic
% Define an error variable (0 = ok, 1 = error).
Error = 0;
% Open file
fid = fopen('alleaks_3.txt'); % Open .txt file for all axle vehicles.

% Check if open was successful
if fid == -1
% Open failed
    Error = 1;
    disp ('ERROR open');
else
% Open was successful ==> read line by line until end-of-file (eof).
disp ('Read file and split lines into elements');
linecounter = 1;
while feof(fid) == 0
    tline = fgets(fid);
    % Convert European ',' in numbers into English '.' representation.
    for index = 1:length(tline)
        if tline(index) == ','
            tline(index) = '.';
        end
        if tline(index) == ''
            tline(index) = 0;
        end
    end
end
clear index;
% Delete the headlines and
% separate the single entries,
% using the delimiter '\t' (tabulator)
if (linecounter > 0 )
    ValuesCellMatrix(linecounter,:) = strsplit (tline, '\t');
    %disp(tline);

    linecounter = linecounter + 1;
end
end
fclose(fid);
clear ans;
clear linecounter;
clear tline;
end

% Converting strings to numbers.
SizeOfValuesCellMatrix = size(ValuesCellMatrix);
Values = zeros (SizeOfValuesCellMatrix(1,1),SizeOfValuesCellMatrix(1,2)-
1);
for RowCounter=1:SizeOfValuesCellMatrix(1,1)
    for ColCounter=1:SizeOfValuesCellMatrix(1,2)
        Values(RowCounter,ColCounter) =
str2double(ValuesCellMatrix{RowCounter,ColCounter});
    end
end

```

```

    end
end
clear ColCounter;
clear RowCounter;
clear ValuesCellMatrix;

% Make new matrices for the right numbers that are going to be used.
matrise_540032 = [];
matrise_540031 = [];
matrise_540109 = [];

% Find the size to know what to use in the loops.
[m n] = size(Values);

% Pick the correct numbers and put them in their corresponding matrices.
for ii = 1:m
    % Check for the correct WIM and that the static weight is different
    % from zero.
    if Values(ii,1) == 540032 && Values(ii,2) ~= 0
        % Add to new matrix.
        matrise_540032 = [matrise_540032; Values(ii+3,2) Values(ii,2)];
    end
end

for iii = 1:m
    if Values(iii,1) == 540031 && Values(iii,2) ~= 0
        matrise_540031 = [matrise_540031; Values(iii+2,2) Values(iii,2)];
    end
end

for iiii = 1:m
    if Values(iiii,1) == 540109 && Values(iiii,2) ~= 0
        matrise_540109 = [matrise_540109; Values(iiii+1,2)
Values(iiii,2)];
    end
end

% Check sizes.
[xx_540032,yy_1740104] = size(matrise_540032);
[xx_540031,yy_1740104] = size(matrise_540031);
[xx_540109,yy_1740104] = size(matrise_540109);

% Create empty matrices.
error_540032 = [];
error_540031 = [];
error_540109 = [];

% Calculate the error.
for aa = 1:xx_540032
    error_540032(aa) = (matrise_540032(aa,2) -
matrise_540032(aa,1))*100/matrise_540032(aa,1);
end

for aaa = 1:xx_540031
    error_540031(aaa) = (matrise_540031(aaa,2) -
matrise_540031(aaa,1))*100/matrise_540031(aaa,1);
end

```

```
for aaaa = 1:xx_540109
    error_540109(aaaa) = (matrise_540109(aaaa,2) -
matrise_540109(aaaa,1))*100/matrise_540109(aaaa,1);
end

% Calculate the mean and standard deviations of the errors.
mean_540032 = mean(error_540032);
std_540032 = std(error_540032);

mean_540031 = mean(error_540031);
std_540031 = std(error_540031);

mean_540109 = mean(error_540109);
std_540109 = std(error_540109);

% Perform a linear regression and acquire the incline and constant term.
p_540032 = polyfit(matrise_540032(:,1),matrise_540032(:,2),1);
p_540031 = polyfit(matrise_540031(:,1),matrise_540031(:,2),1);
p_540109 = polyfit(matrise_540109(:,1),matrise_540109(:,2),1);
```

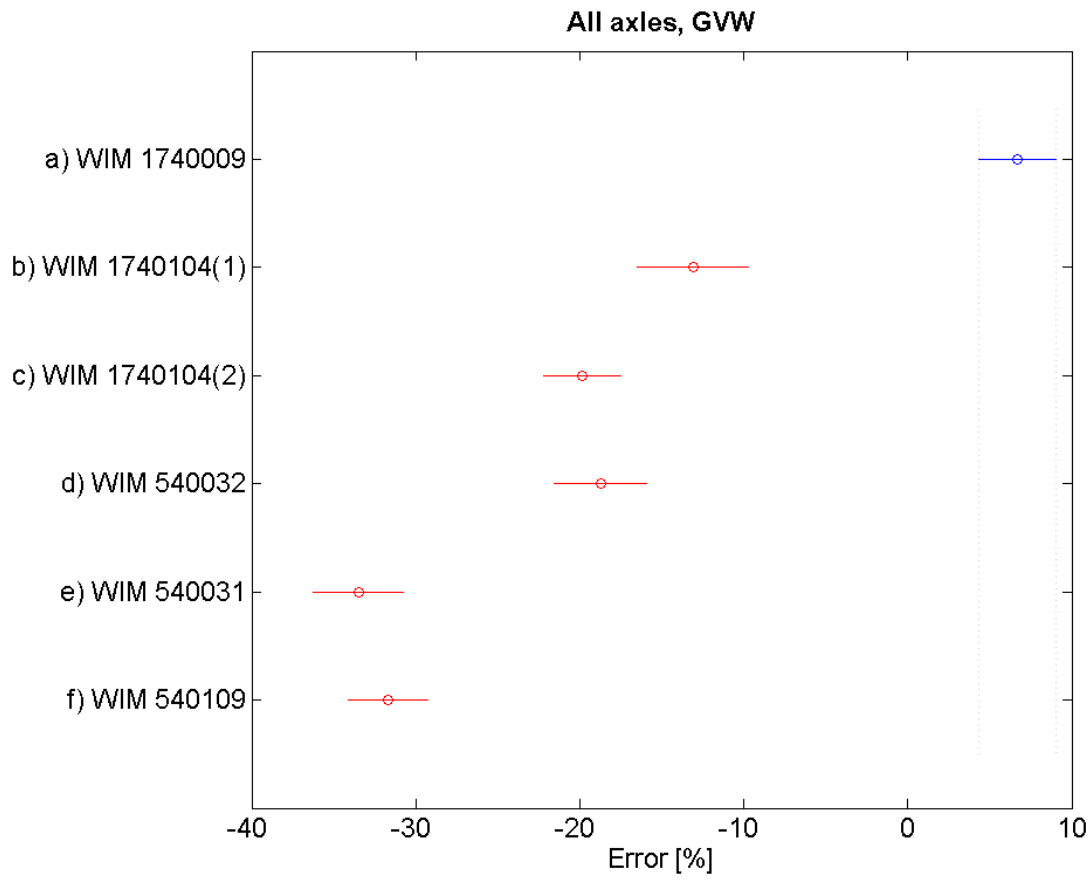


Figure 3-1: ANOVA from all axles, GVW



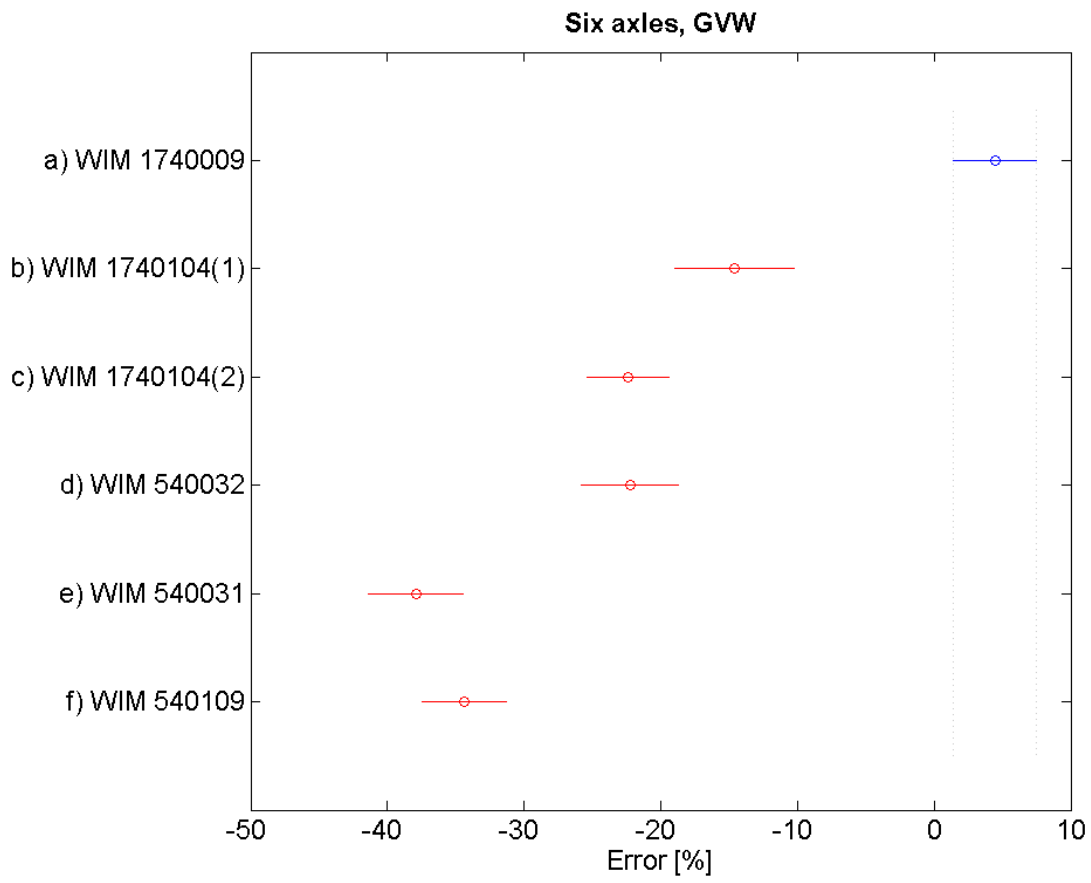


Figure 3-2: ANOVA from six axles, GVW

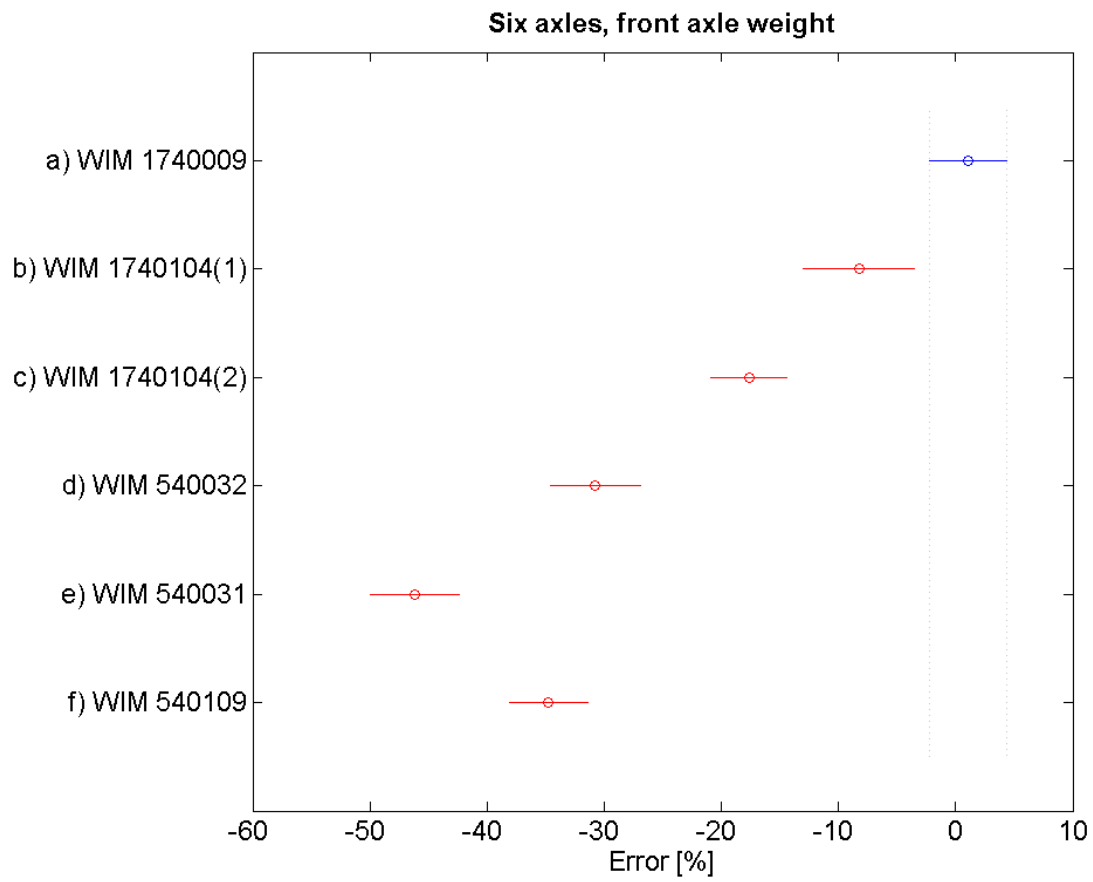


Figure 3-3: ANOVA from six axles, front axle weight.

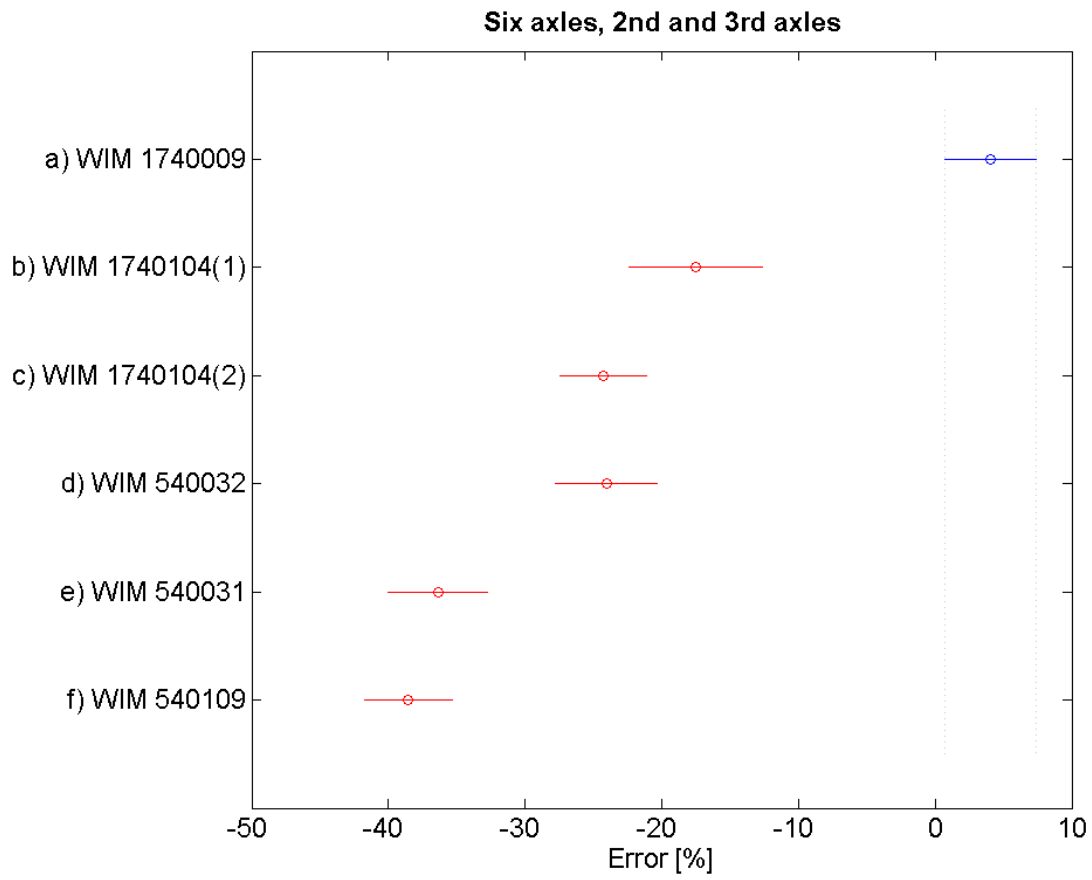


Figure 3-4: ANOVA from six axle, 2<sup>nd</sup> and 3<sup>rd</sup> axles.

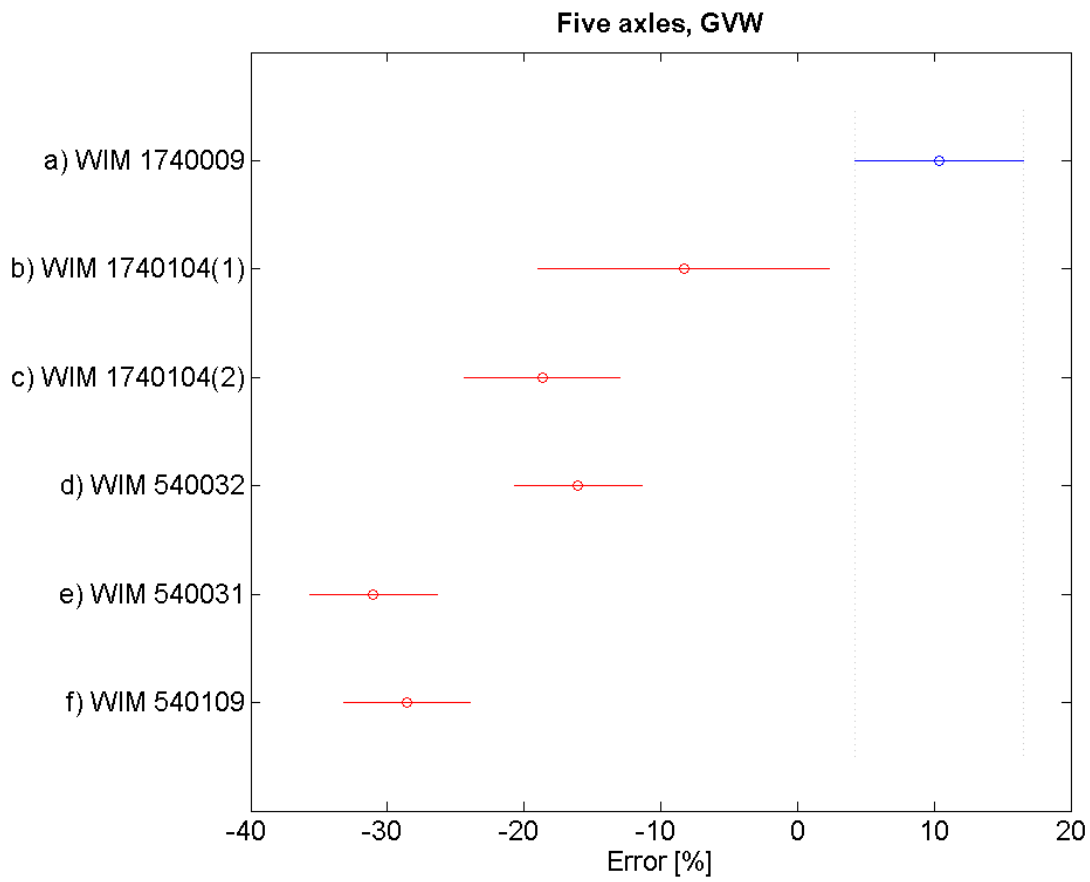


Figure 3-5: ANOVA from five axles, GVW. The graphical confidence interval of b) is faulty by some reasons, but the real 95 % confidence interval is from -12,83 % to- 3,82 %.