# APPLICATION OF ARTIFICIAL INTELLIGENCE TO OVERLOAD CONTROL


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## ABSTRACT

High quality road infrastructure is essential to support economic growth for any landlocked region, confirmed by the fact that 79% of South African goods use road transport. Protection of the road infrastructure is implemented by means of overload control monitoring at Traffic Control Centres (TCCs) on freight corridors linking ports with economic hubs. As these systems lack the available information to support intelligent decision-making, 75% to 85% of statically weighed vehicles are legally loaded, resulting in unnecessary wastage of time and fuel. This paper proposes an intelligent weigh-in-motion (IWIM) algorithm aiming to decrease unnecessary static weighing of vehicles through data sharing between TCCs combined with intelligent data interpretation. Several Artificial Intelligence (AI) models were evaluated for their ability to decrease static weighing of vehicles while not increasing the number of overloaded vehicles allowed to proceed on the corridor. We found that a Random Forest Tree model produced the best performance to differentiate between overloaded and legal vehicles, achieving an average improvement of 65.83% in terms of vehicles to be statically weighed when compared to the current rule-based system. Implementation of the IWIM concept can therefore have a significant positive impact for all stakeholders involved in the freight movement process.


## 1. INTRODUCTION

Landlocked regions are dependent on road and rail transport to facilitate supply chain operations (PWC, 2013), (Hoffman et al., 2013). Due to declining rail infrastructure over the past decades (Marcay, 2013; Van der Mescht, 2006; Jorgensen, 2013; Daniel, 2022; Dumisa, 2022; Williams, 2021) road transport is the predominant means of land transport for import and export goods for landlocked regions with 79% of delivery by road and 21% by rail (Jorgensen, 2013). The quality of the national road network has a huge impact on the effectiveness of trade corridors that link areas of production and consumption with seaports. Road infrastructure (Hoffman et al., 2013), border post operation (Bhero & Hoffman, 2014), and regional law enforcement efficiency is of utmost importance to the region's supply chains (Bosman & D'Angelo, 2011). It must thus be ensured that road infrastructure is protected using intelligent methods that can reconcile streamlined trade flows with effective law enforcement.

### 1.1 Overload Legislation

The protection of road infrastructure is achieved by government regulations that limit the maximum loading capacity of axles, Gross Vehicle Mass (GVM), and load limits of tyres of any vehicle traveling on public roads (National Department of Transport Republic of South Africa, 2004). These values are confirmed by SANRAL's annual reports with maintenance cost stated as ZAR 6,276 billion for 2018/19 financial year and ZAR 6,984 billion for



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2017/18 (SANRAL, 2019). This figure has grown to R 7,270 billion in 2021/22 (Sanral, 2022). This only reflects the cost of road repairs and does not consider the negative impact of poor road conditions on the quality of life of the general population in terms of life safety and increased vehicle maintenance costs (BusinessTech, 12 February 2022). There are 17 classifications of vehicles for the purpose of overload control, that range from motorcycles to trucks with various axle configurations (Smith & Visser, 2001; Mikros, 1998). Legislation allows for a specific maximum permissible mass per vehicle type applicable for South African roads.

## 1.2 Impact of Overloaded Vehicles

Overloading of vehicles occur to generate additional income on a trip. Studies have shown that 60% of road damage can be caused by only 15 - 20% of vehicles being overloaded (CSIR, 1997). Furthermore, vehicles overloaded by 20% can decrease a road surface lifetime by more than 50% (Salama et al., 2006). The operating cost of heavy vehicles tends to increase by 12.8% when vehicles operate on a deteriorated road infrastructure (Steyn & Haw, 2005). As overloaded vehicles operate outside design specifications of vehicle manufacturers, these vehicles have an increased chance to be involved in accidents (National Department of Transport Republic of South Africa, 2004). The annual cost due to road accidents has been estimated to be ZAR 142.95 billion that equates to 3.4% of South Africa's GDP (Roux & Labuschagne, 2016). While only 4.8% of accidents involve heavy vehicles, these accidents, some of them caused by overloading, cause many fatalities when they do occur (Stoltz, 2016).

## 1.3 Traffic Control Centres

The enforcement of overload control rules is implemented at TCCs (Traffic Control Centres) situated on major freight corridors in South Africa. South African National Roads Agency SOC Ltd (SANRAL) has 13 TCCs that are operated by toll concessionaires and 16 satellite stations (SANRAL, 2017, 2018, 2019). Most TCC designs include a screener lane with a WIM (weigh-in-motion) scale that directs a vehicle to the static scale if a weight threshold is triggered. As WIM scale values deviate as much as 16% from the static scale value for the same vehicle, only static scale measurements can be legally used to prosecute an overloaded vehicle. The status quo classification rule that is applied at existing TCC systems is as follows:

- The axle configuration of the vehicle is first determined based on the consecutive sets of wheels passing over the WIM scale.
- For each type of axle configuration, a specific threshold (typically 5-10% below the legal limit) is applied; should this threshold be exceeded, the system will determine that the vehicle is potentially overloaded and should be weighed statically at a scale forming part of the same TCC.
- If the result of the static weighing of the vehicle indicates that it is over the legally allowed weight limit for that axle configuration the owner of the vehicle may be prosecuted, and the vehicle may be impounded until its weight has been corrected.
- It is therefore possible that a vehicle that is within the legal weight limits will trigger the WIM scale rule that will guide it to the static scale. As many transporters load vehicle to very close to the legal weigh limits, the situation currently exists where 80-85% vehicles triggering the WIM scale rule are in fact not overweight and are therefore unnecessarily guided to the static scale, based on information extracted from SANRAL static scale reports.

The above discussion indicates that the current overload control system contains a specific inefficiency: the different TCCs work in complete isolation from the TCCs up- or downstream on the same corridor (Hoffman & de Coning, 2014), (Hoffman et al., 2013). Avoidable delays often occur for legally loaded vehicles that are loaded close to the maximum loading capacity as such vehicles triggers the WIM threshold at several consecutive TCCs on its journey. This results in multiple static weighing of vehicles loaded close to the legal limit during the same trip, causing multiple delays. This represents a significant negative impact on the economy, taking into account that around 1.7 to 1.8 million vehicles are statically weighed annually in South Africa (SANRAL 2017, 2018, 2019) and that each stop results in direct fuel and tyre costs of more than R200, with even higher costs resulting from lost time (Hoffman & de Coning, 2014). Large numbers of legally loaded vehicles that are directed to the static scale often back up onto the highway before being weighed, providing overloaded vehicles with the opportunity to skip the queue at a TCC.

### 1.4 Artificial intelligence Applications

AI techniques are implemented to make a machine think and behave intelligently (Joshi, 2017; Campesato, 2020). It is a mechanism to process large amounts of data, more than what a human can process, in order to extract some knowledge to improve real-world and real-time decision making (Joshi, 2017; Campesato, 2020). AI techniques have improved over the last few decades and have become a common occurrence without being obvious to the general public (de Raedt et al., 2016). Within the field of over overload control AI applications have been used to predict static scale weights from WIM weights (Benedict, 2019). All these applications indicate that an AI application can have significant benefits when implemented on freight corridors as proposed in section 2.

### 1.5 Paper Overview

Section 2 will discuss the proposed system improvements. Section 3 describes the data set that was collected, while section 4 will develop the intelligent weigh-in-motion model that classifies whether a vehicle is overloaded or not by making use of data previously collected on the corridor. Section 5 provides an overview of the AI techniques that were evaluated for use in the IWIM concept. The results are discussed in section 6. Section 7 concludes and discusses planned future work.

## 2. RESEARCH PROBLEM STATEMENT

The objective of this research is to develop an intelligent weigh-in-motion algorithm with the ability to differentiate between legally and illegally loaded vehicles, in the presence of noisy data, to reduce repeated static weighing of vehicles that are legally loaded, while at the same time limiting the number of overloaded vehicles that are allowed to proceed on the corridor. This will be achieved with minimal additional capital outlay and no required TCC layout changes. The IWIM solution will de-isolate the various TCCs by allowing information from previous TCCs to be used in conjunction with information from the WIM scale of the next TCC on the corridor when a decision is made whether to direct a vehicle to the static scale or not.

The IWIM concept will implement a risk management model before it decides whether to guide a vehicle that is detected at a WIM scale to the associated static scale. Instead of basing the WIM scale risk model only on the measurement of the current WIM scale, the proposed new system will incorporate the following information before a decision is made:

- If the identified vehicle has not been weighed statically on the same corridor within a time period equal to the expected travel time on the corridor up to the position where the WIM scale is installed, the status quo rule as explained above will apply.
- If the identified vehicle has been weighed statically before on the same corridor, it will be determined if the vehicle arrived at the current WIM scale within normally expected travel time since the previous instance when the vehicle passed over either a WIM or static scale on the same corridor. If the vehicle significantly exceeded the normal travel time the status quo rule will apply as above.
- If the identified vehicle has been weighed statically before on the same corridor and it arrives within normal travel time, the vehicle class, static weighing record that has already been captured for that vehicle as well as the normalized travel time will be used to determine whether it should be guided to the associated static scale.

## 3. COLLECTION OF DATA

The data fields collected at each TCC will be described from the viewpoint of the second station, called *current station or Station 2*, making use of data from the *previous station, or Station 1,* as input to classify whether a vehicle should be statically weighed at Station 2 or allowed to proceed on the corridor. The list below describes the data to be used as inputs into the IWIM algorithm that will be developed:

- Axle count and vehicle class.
- Station 1 WIM axle weights. WIM GVM, static scale axle weights, static scale GVM and Overload status.
- Station 2 WIM axle weights and GVM.
- Normalized travel time between stations (actual travel time divided by average historical travel time).

An experimental system was installed at the two TCCs that formed part of the investigation (Mantsole & Heidelberg), located on the corridor that links the port of Durban to Johannesburg and onwards to the Beitbridge border post, which is South Africa's busiest road border post for northbound freight traffic. Data provided for WIM and static scales at these sites ranged from 2021-03-01 to 2021-08-31. Only vehicles that visited both TCCs and that did not experience significant delays between the TCCs were used for the study. As Heidelberg is located on the Durban side of Johannesburg, while the Mantsole is located on the Beitbridge side of Johannesburg, many vehicles coming from Durban would first visit depots in Johannesburg before possibly proceeding to Beitbridge; as a result, only a small fraction of vehicles travelled uninterrupted between the two TCCs.

The data statistics are indicated in Table 1. The NB (northbound) data shows an overlap from 2021-04-01 to 2021-08-31 at both sites. Data provided from the WIM data set contained just under 482 000 vehicle weigh entries and just under 152 000 distinct vehicles in the calendar period. The static scale data showed just over 80 000 vehicles statically weighed and just under 35 000 distinct vehicles. The WIM ANPR linking was not always successful, with a NaN (or empty vehicle registration details) entry on just over 56 000 entries additional to the distinct vehicles. At Heidelberg, 15,13% of the NB traffic was directed to the static scale, and 18,04% of the traffic was statically weighed at Mantsole.

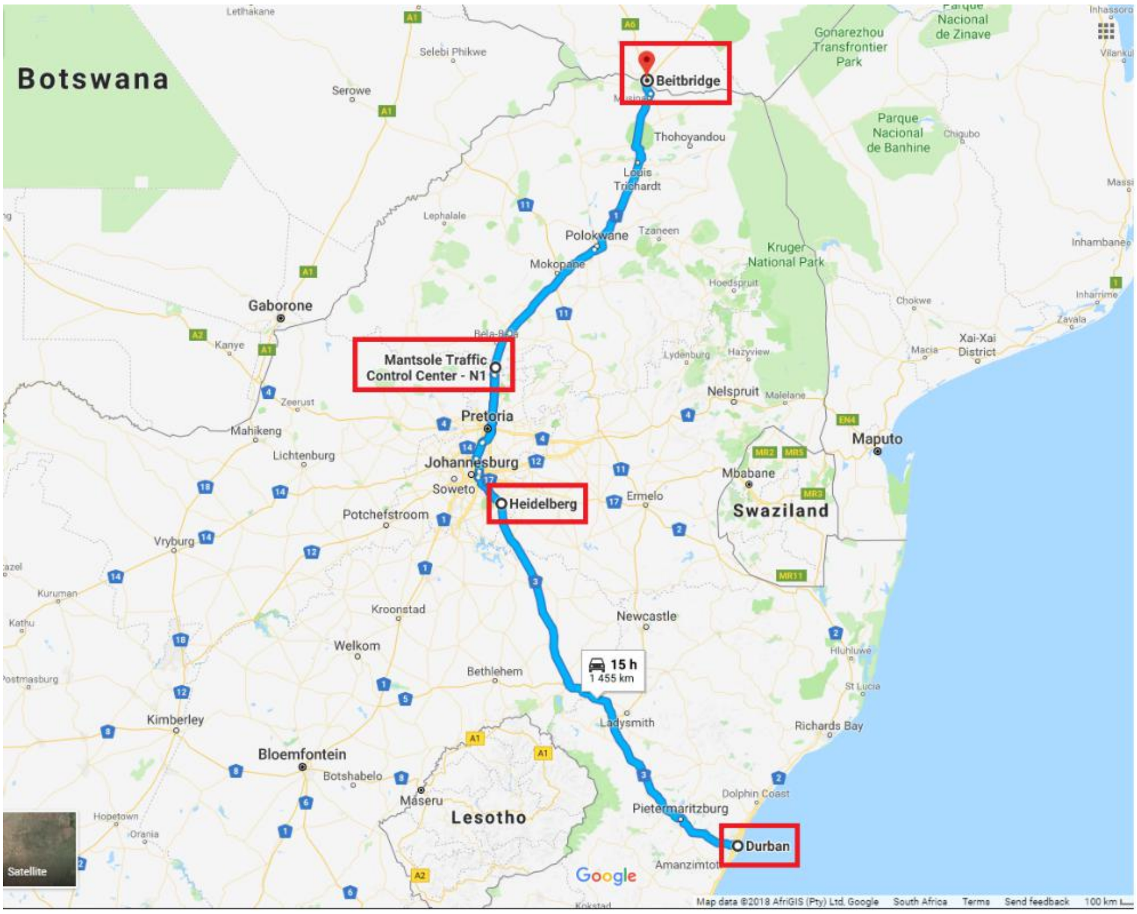


**Figure 1: North-South Corridor from Durban to Beitbridge**

**Table 1: Data set statistics**

| **WIM** | **Heidelberg NB** | **Mantsole NB** | **Mantsole SB** | **Heidelberg SB** |
|---|---|---|---|---|
| Minimum date | 01/04/2021 00:01 | 01/04/2021 00:00 | 01/03/2021 00:07 | 01/03/2021 00:02 |
| Maximum date | 31/08/2021 23:59 | 31/08/2021 23:56 | 31/08/2021 23:54 | 31/08/2021 23:52 |
| Entry count | 233 392 | 248 537 | 279 114 | 272 572 |
| Distinct vehicle count | 76 469 | 99 815 | 82 296 | 71 187 |
| NaN values | 45 000 | 11 032 | 18 238 | 51 455 |
| **Static** | **Heidelberg** | **Mantsole** | **Mantsole** | **Heidelberg** |
| Minimum date | 01/04/2021 00:25 | 01/04/2021 00:15 | 01/03/2021 00:20 | 01/03/2021 02:19 |
| Maximum date | 31/08/2021 23:36 | 31/08/2021 23:49 | 31/08/2021 23:54 | 31/08/2021 23:53 |
| Entry count | 35 322 | 44 845 | 37 336 | 34 585 |
| Distinct vehicle count | 14 456 | 20 410 | 17 057 | 17 449 |

The SB (southbound) data has an overlap in data from 2021-03-01 to 2021-08-31 at both sites. The WIM data set contained just over 551 000 vehicle weigh entries and just over 153 000 distinct vehicles in the calendar period. The static scale data showed just under 72 000 vehicles statically weighed and just over 34 000 distinct vehicles. SB traffic had 13,38% directed to the static scale at Mantsole and 12,69% at Heidelberg.

The next step in the process was to reliably link the data captured by the two TCCs. The process of linking vehicle records for WIM and static scales was as follows:

1. Determine vehicle registration to be used as identifier.
2. Search following site records for the same identifier.
3. Determine the time difference between entries.
4. Store values of vehicles that travelled between the sites in the past 24 hours.

In this way we were able to link a total of 3,167 observations between the different TCCs which could be used for model training purposes. The linked data set had a total of 17 vehicles or 0,54% that were not overloaded at site 1 and overloaded at site 2, while 20 vehicles or 0,64% were overloaded at site 1 and not overloaded at site 2.

## 4. DEVELOPMENT OF THE IWIM CLASSIFIERS

The purpose of the proposed IWIM concept is to decide if the vehicle must be statically weighed or not at Station 2. The simplest method to implement this would be to use a fixed set of rules to apply the logic of overload control regulations as described above. The state flow of a rule based IWIM system required the determination of optimal threshold values for the decisions to be taken to distinguish between vehicles that should be guided to the static scale and vehicles that should be allowed to proceed on the corridor. If the input values are random in nature rather than assuming fixed values, a single noisy input value may cause the rule-based technique to branch off in a wrong direction, as a rule-based technique considers the various inputs one at a time.

The first element of uncertainty for the IWIM is the time that a vehicle, that was still legally loaded at the previous TCC, should be allowed to travel from the previous static weigh point to the current TCC to still be regarded as low risk, given that vehicles do not always travel at the same speed. A 2$^{nd}$ element of uncertainty is how close each axle weight, as measured by the last static scale, may be to the overload limit before the vehicle will be regarded as high risk, given that the load may have shifted during the trip, resulting in changes to the axle loads. A 3$^{rd}$ element of uncertainty is the current WIM scale reading, that is known to be inaccurate. It is therefore not obvious when the current WIM reading should be used to override a previous static scale reading for the same vehicle.

More advanced classification techniques, that process all input data in parallel, have been shown to have superior classification abilities when fed with noisy data compared to simple rule-based classifiers. This is because the presence of noise in one input variable can to some extent by compensated for by the other inputs that influence the outcome (Joshi, 2017). By training such techniques on a specific data set and then testing them on another unseen data set, it will be possible to determine with a high degree of certainty which of the techniques will produce the most reliable classifications in a real-world scenario.

The process to train AI based classifiers for the IWIM application is described below:

- Each observation in the data set consists of the set of inputs as explained in the previous section, as well as an output variable, which is the true overloaded status as determined by the static scale of Station 2. During training of the models this output is used as target variable that the classifier should produce when fed with the corresponding input data.
- The total available data set is then split into a training and test dataset, using an 80/20 split. This will allow the classifiers to be tested for their ability to generalize.

- To prevent overfitting of the trained model, a portion of the training data is used as validation set. The training process is terminated once the error on the validation set has reached its minimum value. This model is then tested on the testing dataset to determine how accurate it truly is on unseen data.
- A confusion matrix is generated, containing four possible outcomes:
  - True Positive (TP) results when the output was set as overloaded, and the model predicted the same.
  - True Negative (TN) results when it was not overloaded, and the model predicted the same.
  - False Positive (FP) results when the model prediction is overloaded but it was not overloaded.
  - False Negative (FN) results when the model incorrectly predicted the vehicle is not overloaded while it was overloaded.

This is depicted in Figure 2 below.

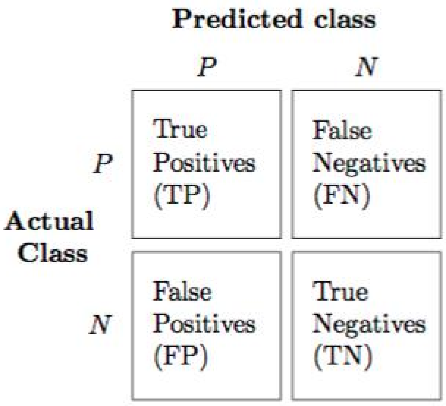


**Figure 2: Sample confusion matrix layout for a binary classification model**

- Accuracy is defined as the sum of true positives and true negatives divided by the total number of observations. It is important to determine how many vehicles were incorrectly sent to the static scale (which will waste time), or to the corridor without prosecution (which will cause road damage) as this reflects the negative impact of the inefficiencies of the overload control system.
- In this case we had 3,105 linked observations of legally loaded vehicles and only 37 cases of overloaded vehicles. In case of such an unbalanced training set the model will tend to train in such a manner that all observations are classified into the more populous class, which will result in a high classification accuracy but with all overloaded cases in the wrong class. It was therefore necessary to artificially increase the size of the overloaded class by repeating its observations in the training set. In our case we increased the number of overloaded observations to 272 samples through duplication.
- We furthermore normalised the continuous input variables (axle weights. GVM and travel time), while for categorical inputs (vehicle class) we used One Hot Encoding.

## 5. AI TECHNIQUES

The AI models tested in this study to improve the performance of a simple rule-based model are logistic regression, Random Forest Trees (RFTs), and multi-layer perceptron (MLP) Artificial Neural Networks (ANNs). Logistic regression is commonly used to model input-output relationships where the outputs are categorical, as in this case. We tested 3 different solvers, using a maximum number of iterations of 1500:

- Limited-memory Broy-den–Fletcher–Goldfarb–Shanno.
- A Newton method using an exact Hessian matrix.
- Large Linear Classification.

The RFT constructs a tree to determine the output value from the inputs. Several hyper parameters that served as input into selection of the models were investigated: the n estimators, maximum depth, and minimum sample splits. The maximum depth the branches would generate was set to either 10 or 15. The n estimator, which is the maximum number of trees generated in the forest, was set to 50. The RFT models tested were therefore as follows:

1. Random forest tree 1: default.
2. Random forest tree 2: maximum depth = 15, n estimators = 50.
3. Random forest tree 3: maximum depth = 10, n estimators = 50.

MLPs are the most common type of ANN used for classification purposes. The input layer was defined based on the 79 input variables. Two hidden layers were added, as it was established that increased hidden layers did not influence the accuracy of the models. The hidden layer units were selected as double the number of input units; this is often used as a standard industry implementation. The dropout was varied between the data sets, with training batch size chosen at 25. We found that many epochs did not change the results so 10 epochs were chosen to limit processing times. Three ANN models were trained on the data sets:

1. ANN 1: 20% dropout applied.
2. ANN 2: 40% dropout applied.
3. ANN 3: No dropout applied.

## 6. RESULTS

To create a performance benchmark against which we can compare improved IWIM algorithms based on the above techniques, we first calculated the percentage of linked vehicles that were classified as overloaded and not overloaded by the current system employed at TCCs. The results in Table 2 indicate that within the available training set almost 98% of legally loaded vehicles are sent to the static scale.

**Table 2: Status quo rule-based performance**

| | **Actual** | **Predicted** |
|---|---|---|
| Observations | 3,122 | 3,122 |
| Overloaded | 17 | 3,076 |
| Not overloaded | 3,105 | 46 |
| % Overloaded | 0.54 | 98.53 |
| % Not overloaded | 99.46 | 1.47 |
| % Not overloaded sent to static scale | | 97.98 |

The confusion matrix for the status quo rule-based classifier, using a WIM threshold of 90% of the legal limit, is displayed in Table 3 below. Accuracy is a mere 2.01% for a WIM threshold of 0.9. The large number of vehicles incorrectly sent to the static scale (false positives) using this status quo rule-based technique can be reduced by increasing the WIM threshold from 90% of the legal limit to a higher value. This however results in some of the overloaded vehicles being sent to the corridor due to WIM errors, as displayed in Table 4 where the WIM threshold was increased to 105.4% of the legal limit. While accuracy is increased to 71.0%, this is achieved at the cost of allowing a significant number of overloaded vehicles onto the corridor. It is clear that a more suitable approach is required.

**Table 3: Confusion matrix for status quo rule-based classification with WIM threshold of 0.9**

| | |
|---|---|
| True Positive | False Negative |
| 17 | 0 |
| False Positive | True Negative |
| 3059 | 46 |

**Table 4: Confusion matrix for status quo rule-based classification with WIM threshold of 1.054**

| | |
|---|---|
| True Positive | False Negative |
| 5 | 12 |
| False Positive | True Negative |
| 893 | 2212 |

Due to the random nature of the AI models the training process was repeated several times for each model type, and the average and standard deviation of model errors were calculated in each case. Results are displayed in Table 5 below. The RFT models had the best false negative performance average at 0,08% and an accuracy of 99.6%. ANN model 3 had the next best false negative performance at 0,60% with an average accuracy of 98.6%. The logistic regression models had an accuracy of 94.3% and an average false negative of 5,53%.

**Table 5: Accuracy of AI techniques trained using Padded Linked data set**

| | Max | Min | Ave | Stdev |
|---|---|---|---|---|
| ANN 1 | 98,69% | 94,18% | 96,14% | 1,88% |
| ANN 2 | 98,75% | 93,10% | 95,10% | 2,50% |
| ANN 3 | 98,92% | 98,24% | 98,59% | 0,33% |
| Log reg 1 | 99,14% | 92,02% | 94,28% | 3,27% |
| Log reg 2 | 99,14% | 92,02% | 94,28% | 3,27% |
| Log reg 3 | 99,17% | 92,02% | 94,27% | 3,29% |
| RFT 1 | 100,00% | 98,69% | 99,63% | 0,63% |
| RFT 2 | 100,00% | 98,75% | 99,65% | 0,60% |
| RFT 3 | 100,00% | 98,81% | 99,66% | 0,57% |

As RFT and ANN outperformed logistic regression, we analysed the results of the best models for those techniques in more detail. In Table 6 below we display the RFT results achieved for both the cases with and without expanding the training set with additional observations for the overloaded classes. It is clear that the expansion of the data set as explained in the previous section is essential to prevent the technique from predicting many false positives. The results for the expanded training and test sets indicate similar performance for both sets, providing evidence that the technique generalized well. Table 7 displays the confusion matrix for the expanded combined training and test set. Only one classification mistake was made, and no overloaded vehicles were classified as legal.

**Table 6: Results for the random forest tree trained on the Padded Linked data set**

| | True Pos | True Neg | False Pos | False Neg | Total |
|---|---|---|---|---|---|
| Unexp | 7 | 3074 | 31 | 10 | 3122 |
| Expanded | 272 | 3419 | 1 | 0 | 3692 |
| Train | 208 | 2745 | 0 | 0 | 2953 |
| Test | 64 | 674 | 1 | 0 | 739 |

**Table 7: Random forest tree model confusion matrix**

| | |
|---|---|
| True positive | False Negative |
| 272 | 0 |
| False Positive | True Negative |
| 1 | 3419 |

Table 8 and Table 9 display similar results for the ANN technique. While the performance is satisfactory, the number of incorrect classifications was significantly higher compared to the RFT technique, and 32 cases of overloaded vehicles were classified as legally loaded.

**Table 8: Results for the artificial neural network trained on the Padded Linked data set**

| | True Pos | True Neg | False Pos | False Neg | Total |
|---|---|---|---|---|---|
| Unexp | 12 | 3073 | 32 | 5 | 3122 |
| Expanded | 240 | 3392 | 28 | 32 | 3692 |
| Train | 179 | 2722 | 23 | 29 | 2953 |
| Test | 61 | 670 | 5 | 3 | 739 |

**Table 9: Artificial neural network model confusion matrix**

| | |
|---|---|
| True positive | False Negative |
| 240 | 32 |
| False Positive | True Negative |
| 28 | 3392 |

All 3 AI techniques drastically improved on the primary weakness of the status quo technique, namely false positive (classifying legally loaded vehicles incorrectly as overloaded). The primary selection criterion between these models was therefore false negatives (sending overloaded vehicles incorrectly to the corridor). RFT was the clear winner in that respect, as it made no such classification mistakes.

To consider practical system deployment issues the time required to train each of the models was measured. The ANN model training and testing was completed in 29 minutes for all the simulation data sets. The RFT model training and testing was completed in 37 minutes. The processing power for training a RFT only requires a central processing unit (CPU) while the ANN requires an additional graphics processing unit (GPU) for training. This would increase hardware complexity and deployment costs. Based on all considerations the RFT technique therefore appears to be the most suitable classification model for this problem.

## 7. CONCLUSIONS AND FUTURE WORK

There are significant inefficiencies in existing overload control operations resulting from the fact that the system does not share information between TCCs, causing most legally loaded vehicles to be subjected to repeated static weighing. In this paper we proposed a novel overload control method that shares data between stations to allow more intelligent decisions to be made about the necessity of a vehicle to be statically weighed. As the available input data is noisy, it is not trivial to make correct decisions, as indicated by the results achieved with the status quo rule-based method. This justified the use of AI techniques to improve the quality of decision-making. The proposed concept implements intelligent decision-making at the WIM scale, to decide which vehicles to direct towards the static scale. The available model inputs include the weight measurements at the previous static scale and the current WIM scale, as well as travel time from the previous scale.

Our results indicate that ANN and RFT based classification models can significantly improve on the performance of the status quo rule-based method. The RFT model has the highest accuracy and makes the least incorrect decisions to direct legal vehicles to the static scale and overloaded vehicles to the corridor.

Future work should include the operational deployment of the IWIM method to determine if the results as reported in this paper can also be achieved in practice.

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