ICWIM8

8th International Conference on Weigh-in-Motion

Editors : Bernard Jacob & Franziska Schmidt

Prague, May 19-23, 2019

Acknowledgement

The editors acknowledge the members of the International Scientific Committee ISC-WIM for the abstract and paper reviews, and all the authors for their valuable contributions.

They also ackowledge Mrs Joëlle Labarrère for developing and publishing the electronic proceedings.

Information on:

ICWIM8 Conference web site: http://www.is-wim.org/icwim8

© ISWIM, Zurich, Switzerland & Ifsttar, Paris, France, 2019

International Society for Weigh-In-Motion

EMPA, Überlandstrasse 129

CH-8600 Dübendorf

Switzerland

Institut Français des Sciences et Technologies des Transports, de l'Aménagement et des Réseaux

14-20 bd Newton

77447 Marne-la-Vallee Cedex

Proceedings of the 8th International Conference on Weigh-In-Motion

Editors: Bernard Jacob & Franziska Schmidt

Zürich, Switzerland, International Society for Weigh-In-Motion
Paris, France, Institut Français des Sciences et Technologies des Transports, de l'Aménagement et des Réseaux Publications

Keywords: Heavy vehicles, heavy vehicle technology, lorries, truck equipment, road transport, Vehicle classification, weigh-in-motion, WIM, WIM technology, WIM systems, weight measurement, standards, specification, vehicle operation, vehicle control, weight and size enforcement, size and weight evaluation, traffic loads, road safety, freight mobility, road operation, road pricing, road, pavements, bridges, vehicle-infrastructure interaction, environment, testing, measurements, data quality, data management, regulations, enforcement, sensors, accuracy, durability, databases, tests.

Table of contents

Preface

The 8th International Conference on Weigh-In-Motion (ICWIM8) comes back to Europe, after two editions in North and Latin America. It is the first ICWIM organized in Central (former Eastern) Europe. The local organization is subcontracted to the Czech Transport Research Centre (Centrum Dopravniho Vyzkumu, CDV). IFSTTAR (French Institute of Science and Technology of Transport, Planning and Networks) brought a strong support to the International Society for Weigh-In-Motion (ISWIM) organizing a successful conference and leading the International Scientific Committee (ISC). Three International organizations are also partners of this conference: the International Transport Forum of the OECD (ITF), the World Road Association (PIARC) and the Forum of European Highway Research Laboratories (FEHRL).

ICWIM has a rich history, with a series of 8 conferences held in 4 continents: Zürich (1995), Lisbon (1998), Orlando (2002), Taipei (2005), Paris (2008), Dallas (2012), Foz do Iguaçu (2016) and now Prague (2019). Two of these conferences (2002 and 2012) were combined with NATMEC (North American Travel Monitoring Exhibition and Conference), and one (2008) with HVTT (Heavy Vehicle Transport Technology) conferences. ICWIM7 (2016) was combined with a PIARC International seminar.

ICWIM8 is held as a series of 8 dedicated sessions with fully peer reviewed papers published in these proceedings, and two panel discussions. ICWIM8 also includes for the first time an end-user series of sessions specifically designed for practitioners to be exposed to the benefits, uses and value that mass data brings.

The conference addresses the broad range of topics related to on-road and in-vehicle WIM technology, its research, installation and operation and use of mass data across variable end-uses. Innovative technologies and experiences of WIM system implementation are presented. Application of WIM data to infrastructure, mainly bridges and pavements, is among the main topics. However, the most demanding application is now WIM for enforcement, and the greatest challenge is WIM for direct enforcement. Most of the countries and road authorities should ensure a full compliance of heavy vehicle weights and dimensions with the current regulations. Another challenging objective is to extend the lifetimes of existing road assets, despite of increasing heavy vehicle loads and flow, and without compromising with the structural safety. Fair competition and road charging also require accurately monitoring commercial vehicle weights by WIM.

WIM contributes to a global ITS (Intelligent Transport System) providing useful data on heavy good vehicles to implement Performance Based Standards (PBS) and Intelligent Access Programme (IAP, Australia) or Smart Infrastructure Access Programme (SIAP).

The conference reports the latest research and developments since the last conference in 2016, from all around the World. More than 150 delegates from 33 countries and all continents are attending ICWIM8, mixing academics, end users, decision makers and WIM vendors. An industrial exhibition is organized jointly with the conference.

We greatly appreciate the support of the major sponsors of the conference: Camea, Cross, Intercomp, International Road Dynamics (IRD), Kistler AG, Q-Free and Vanjee.

Bernard Jacob
Vice-president Science of ISWIM
International Scientific Committee Chair
IFSTTAR, France

Franziska Schmidt
International Scientific Committee Vice-chair
IFSTTAR, France

International Society for Weigh-in-Motion (ISWIM)

The International Society for Weigh-In-Motion (ISWIM), an international not-for-profit organization based in Switzerland, was born in 2007 and officially launched in 2008, to welcome all with a common interest in WIM – both on-road and in-vehicle. It supports advances in WIM technologies and promotes more widespread use of WIM and its widespread applications including the use and benefits of mass information.

ISWIM brings together three distinctive groups:

- users
- researchers, and
- vendors of systems for weighing of vehicles in motion.

Organizing WIM conferences and seminars is one major objective. ISWIM has successfully held seven International Conferences on Weigh-in-Motion (namely ICWIM 1 to 7) including Zurich, Lisbon, Orlando, Taipei, Paris, Dallas and Foz-do-Iguazu. In addition, International Seminars have been organized, such as in Florianopolis (Santa Catarina, Brazil) in 2011. Furthermore, ISWIM actively participates in sister organization events including (for 2018 only):

- Intertraffic (20-23 March 2018), Amsterdam, Holland. The workshop on the uses of WIM for Enforcement was held
- NATMEC, a short presentation on ISWIM at the plenary opening session and a 1-hour ISWIM session
- SATC, Southern African Transport Conference and Exhibition (9-12 July 2018), a full day ISWIM workshop was held
- HVTT (2 – 5 October 2018), Rotterdam, Holland. The seminar included a 50-minute ISWIM side event

As part of the outreach program, ISWIM publishes on a quarterly basis the ISWIM Newsletter. The newsletter covers stories from the WIM world including articles from users, academics and vendors.

ISWIM is also active on the Internet through its web site http://www.is-wim.org and is actively involved though its LinkedIn account. The social media offers an International portal for all things WIM, with many resources, such as scientific and technical publications, links to WIM web sites, and facilitates exchanges of WIM experiences. The website hosts the pages of the affiliated vendors forming the Vendor College.

ISWIM has a scientific interest in supporting WIM standardization initiatives such as the recently European standard submitted to the vote of the EU members states by the CEN (European Committee for Standardization). ISWIM is promoting common tests and assessment of WIM systems and WIM applications in exposing end-users to the myriad of uses.

ISWIM consists of individual and corporate members. There is no membership fee for individuals. There is a membership fee for companies and organizations.

ISWIM has widespread individual membership from 73 countries.

The Vendors College consists of 19 members from 13 different countries who all are actively involved in the manufacture and supply of WIM equipment globally. The Vendors College has grown over the years, and still continues to do so, since ISWIM was first formed and is proud to have an active and leading role within the society. The members of the college meet from time to time between the international ICWIM conferences, usually at trade fairs, where members are likely to be attending to discuss pertinent matters relevant to their interests. In addition, the members of the college vote for a presence on the ISWIM board, where they are represented by two of their elected members.". There is a Board of up to 15 members which is elected by the General Assembly of all members.

You are invited to join ISWIM and become an active member of the ISWIM community by signing up on the ISWIM web site: **http://www.is-wim.org.**

Chris Koniditsiotis
President
Australia

Bernard Jacob
Vice-President
Science
IFSTTAR
France

Andrew Lees
Vice-President
End-users
Q-Free
United Kingdom

Lily Poulikakos
Treasurer
EMPA
Switzerland

Deborah Walker
General Secretary
FHWA
United States

Aleš Žnidarič
Information Officer
ZAG
Slovenia

APPLICATION OF DEEP LEARNING TECHNIQUE IN HIGH SPEED WEIGH-IN-MOTION SYSTEMS FOR DIRECT ENFORCEMENT

Received her Ph.D. degree in mechanical engineering from Saskatchewan University of Canada in 2014. She is currently a principal researcher in Fard Iran company where she is working on intelligent transportation system development for direct enforcement.

Received his M.Sc. degree in Electrical Engineering from California state university in 1992. He has been involved in several national and international scientific and technical projects in ITS, precision instrument and metrological areas in Fard Iran company.

Fatemeh HEIDARI
Fard Iran Company
Iran

Morteza POUYAN
Fard Iran Company
Iran

Abstract

Direct Enforcement Weigh-in-motion (WIM) systems are inevitable parts for Intelligent Transportation Systems. Hence, it is essential to have reliable WIM instruments that fulfill standard specifications during operation time. To that effect, two weighing platforms were used in each lane, (3.5~4.5 x 0.98) m.

For a period of more than one year, more than 50,000 trucks from various classifications, in different weigh-station locations, had passed our WIM platforms, were stopped to be weighed statically. Axle, Group of Axles and Gross Vehicle loads of these vehicle were measured utilizing a specially designed static truck scale. So we create invaluable datasets, which in turn, made the WIM systems perform independent of vehicles' suspension system types and road surface quality.

Keywords: weigh-in-motion, data analysis, deep learning technique, direct enforcement.

Résumé

Les sytèmes de pesage à contrôle de sanction automatique sont des éléments essentiels de systèmes de transport intelligents. Ainsi il est important d'avoir des systèmes de pesage remplissant certaines spécifications durant leur durée d'exploitation. Pour cela, deux systèmes de .pesage ont été utilisés, un par voie de circulation

Sur une période de plus d'une anné, plus de 50 000 poids lourds, de différentes silhouettes et de différentes station sde pesage, ont été traités par nos systèmes de pesage pour être pesés en statique. Les poids des essieux, des groupes d'essieux et poids totaux ont été mesurés. Ceci nous . .a permis de créer des données indépendantes des suspension er de la qualité de la surface

1. Introduction

Transportation and Road Ministry of Iran is currently implementing a network of WIM systems deployed throughout the whole country consisting of more than 150 WIM systems. The main reason of using WIM systems is to measure gross, axle, and axle-group weights of trucks to improve road maintenance, infrastructure design, and load limit enforcement. To accomplish this, a national project started to install more than 150 WIM systems in main roads all over the country.

One challenge in WIM system is data analysis method. To date, different approaches have been applied to increase weigh estimation accuracy. For example, (Zhi-feng et. al, 2015) presented particle swarm optimization method to separate the dynamic tire forces contained in axle-weight signal. In order to improve precision of the WIM system data for direct enforcement, there is an urgent need for data analysis methods that can analyze massive data from weighing sensors automatically and provide axles, group of axles and gross vehicle weights accurately. Artificial intelligence techniques, such as artificial neural networks (ANNs), could be used for weight estimation and vehicle classification as well. A neural network approach was developed in (Wang & Flood, 2015) for WIM system. Through the literature review, it was noticed that ANNs are one of the most commonly used classifiers and estimator approach in the intelligent methods. Gonzalez et. al, (2003) reported that applying ANNs outperformed the traditional average-based calibration methods especially with noisy data. ANN-based approaches have been applied for dynamic weighing systems since 1998 by Bahar & Horrocks, (1998) and in many other researches (Baladrón, et. al, 2012, Lin et. al, 2015, Ru, et. al, 2010). The ANN-based approaches reported in literature for dynamic weighing systems have three obvious deficiencies:(1) The features input into neural system are extracted and selected from the measured signals of load sensors (such as load cells), largely depend on shape of the signal and the sampling rate of data acquisition system. (2) The features are selected according to velocity of vehicle passing WIM system. Characteristics of the signal are completely dependent on vehicle velocity. Thus it is necessary to adaptively mine the characteristics hidden in the measured signals to extract appropriate features out of the data. (3) The ANNs commonly developed in intelligent WIM systems have shallow simple architectures, which means having only one hidden layer in an ANN architecture; e.g. (Jiang, et. al, 2012, Lin et. al, 2015). Such simple architectures of ANN may not be able to model nonlinearities of WIM data. Deep learning (DL) technique holds the potential to overcome the aforementioned deficiencies in the dynamic weighing systems. DL refers to a class of machine learning methods, where many layers of information processing stages in deep architectures are used for classification, regression and other tasks (Jia, et. al, 2016). Deep neural networks (DNNs) is applied for sensor signal processing in WIM system. This paper proposes a novel data analysis method to overcome the above-mentioned deficiencies of the ANN-based techniques used in WIM systems. In this method, DNNs are utilized to extract features from weighing sensor (load cell) data and estimate static axle weight. First, unsupervised layer-by-layer learning is used to pre-train data and modify features. Then a supervised learning algorithm is applied to construct the best model for the WIM system. The advantages of the proposed method are summarized as follows. (1) It is able to extract adaptively dominant features from raw data without any dependency to the vehicle velocity. (2) The technique is capable of constructing the nonlinear relationships in the data. So, the proposed algorithm is expected to estimate axle load regardless of vehicle speed, vehicle suspension types and WIM site road roughness. Compared with available methods the proposed approach, is expected to obtain higher axle weight estimation accuracy to establish intelligent WIM (IWIM) system eligible for direct enforcement.

2. Deep learning

DL constructs a high dimensional function via sequences of training to model nonlinear transformations among data. The deep architectures are very large neural networks that can handle huge amounts of data. These large NNs are trained with more and more data to increase their performance. This is generally different to other machine learning techniques that reach a plateau in performance. Deep learning allows for efficient modeling of nonlinear functions. The advantage of deep hidden layers is for a high dimensional input variable, x = (x1, . . . , xp). DNN is able to identify any underlying trends such as those due to spatial repeatability and to consider them in its estimation of labeled value. The Kolmogorov-Arnold representation theorem provides the theoretical motivation for deep learning (Polson, et. al, 2017). The theorem states that any continuous function of n variables, defined by F (x), can be represented as

$$F(x) = \sum_{j=1}^{2n+1} g_j \left(\sum_{i=1}^{n} h_{ij}(x_i) \right) \tag{1}$$

Where g_i and h_{ij} are continuous functions, and h_{ij} is a universal basis, that does not depend on F. For a NN, it means that any function of n variables can be represented as a neural network with one hidden layer and 2n + 1 activation functions.

3. HS-WIM structure

An overview of different sections of the proposed HS-WIM system is shown in Figure 1. The basic structure of the HS-WIM system is composed of four main modules: (1) mechanical components, (2) electrical components, (3) software components and (4) vision components. These four modules are further defined as follows:

Mechanical module: This grouping includes the set of technologies, structures and sensors that receive vehicle axle weight data while passing the system. This section includes load receptors, weighing steel structure, weighing platforms and load cell sensors. The Load cells used in HS-WIM system have maximum error of ±0.02% for static weighing and are class C3 OIML certified. The mechanical module is statically calibrated with dead weights in the factory before installation.

Electrical module: this grouping contains the set of receiving axle load data, converting and digitizing data and pre-filtering components. This module composed of A/D converters, decimate board, pre-filter board, and data logger. All instruments of this section is calibrated in the laboratory before installation and all parts are absolutely interchangeable.

Vehicle identification module: this grouping encompasses motion detection, optical character recognition (OCR), and automatic number plate recognition (ANPR) technologies. The components in this part are such as front view camera, side view camera, IR light, white light and image analysis software.
Software programming module: this grouping provides data analyzing for axle load estimation, library, dataset creation, vehicle detection and vehicle identification techniques. Expanded overview of the proposed HS-WIM system architecture is depicted in Figure 2. The arrows connecting each of the components in Figure 2 illustrate the specific information interfaces for the modules in the architecture. The screening computer integrates data from the modules in the system to screen and identify target vehicles at the road. The data from the overloaded vehicles

and Data Center elements are sent to enforcement center. This information will be used to directly apply enforcement activities on the targeted vehicles.

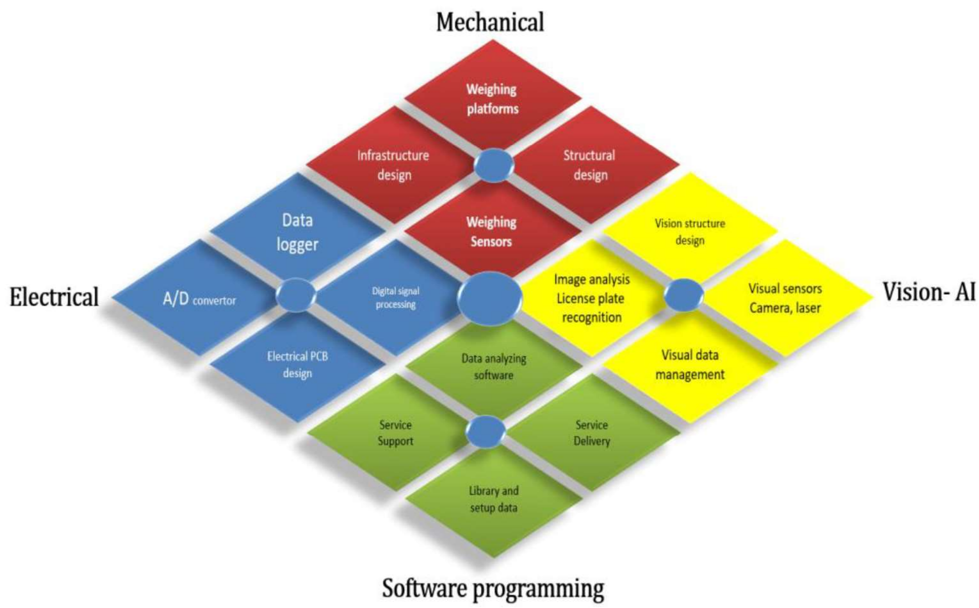

Figure 1 - Four main modules of HS-WIM system

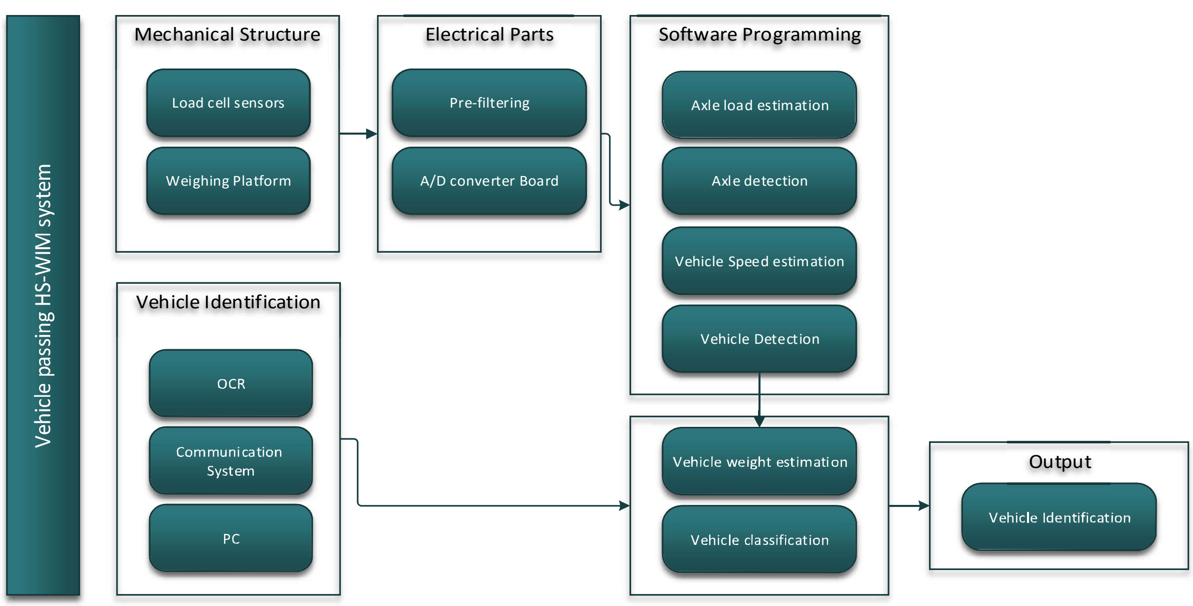

Figure 2 - Expanded hierarchical architecture of HS-WIM system

4. Deep Learning technique for WIM system

Raw data from load cells are received at 63K.Sample/sec rate. This signal may include some random noise as well as vehicle axle weight. One sample data from weighing platforms are shown in Figure 3. The amplitudes and frequencies of dynamic tire forces vary with vehicle speed, load of vehicle, the position of tire load, vehicle suspension type, tire tread type, road roughness, road inclination and so on. It is illustrated that load cell vibration due to dynamic axle impact needs some time to settle down until actual weight signal become stable. We need to estimate static axle load from load cell transient response in HS-WIM system. Since the width (in the direction of traffic flow) of scale platform is 98 cm, so the quicker the vehicles pass the shorter the sampling time and the shorter signal we have. DNNs are trained in three main procedures: (1) Clustering raw data into different clusters according to features characteristics. (2) Pre-training the DNNs layer by layer with unsupervised method called autoencoders. (3) Training DNNs with back propagation (BP) algorithm to minimize square relative error.

5. Clustering

The goal of clustering is identifying classes that all data points into each class have more similarities than data points in other collections. Clustering is the study of algorithm and methods for grouping or classifying objects. A cluster is a collection of data points which are “alike” and data from other collections are not alike (Jain, & Dubes, 1988). This study applied T-Distributed Stochastic Neighbor Embedding (T-SNE) for dimension reduction of data. T-SNE is a nonlinear dimensionality reduction algorithm used for exploring high-dimensional data. It transforms multi-dimensional data to two or more dimensions suitable for human observation. T-SNE technique was applied on Load cell signals; some clusters of features extracted from load cell signal are depicted in Figure 4. One sample result of dimensionality reduction on load cell signal is shown in Figure 5. After application of hierarchical clustering on signal, the clusters are in seven groups depicted in Figure 6. Geometrical characteristics of load cell data were used for clustering; for example, peaks and valleys amplitude ratio and frequency of data are parameters used for clustering. Then data in each cluster are used to train a DNN system separately.

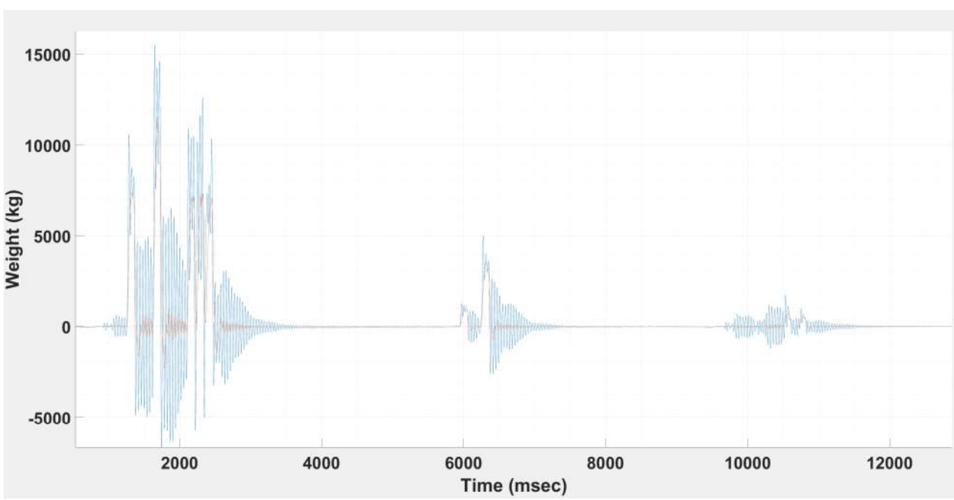

Figure 3 - Sample data from weighing platforms

6. Autoencoder for load cell signal

After clustering signals and identifying alike groups, each collection is sent to Autoencoder (AE) for subject modeling. Features extracted in each cluster are used as input to an AE. An AE is a DNN that has the same dimensions for input and output and all layers are fully connected. In the training phase, the AE is trained by using the same load cell signal as input and also output. An AE can generate highly similar output for trained data, whereas it does not for unfamiliar data.

Therefore, different test sets are used for validation and cross-validation processes. Figure 7 illustrates the proposed method for AE which is a seven-layer AE with one input layer, five hidden layers, and one output layer. Output of each layer is used as an input to the next layer. The training steps continue until the sixth layer autoencoder is trained and the output layer provides the organized features for the load cell signal. In the proposed AE, the pre-training via encoder and decoders helps DNNs learn multiple nonlinear relationships among extracted features. Then the fine-tuning process helps the DNNs estimate static axle weights from load cell signals.

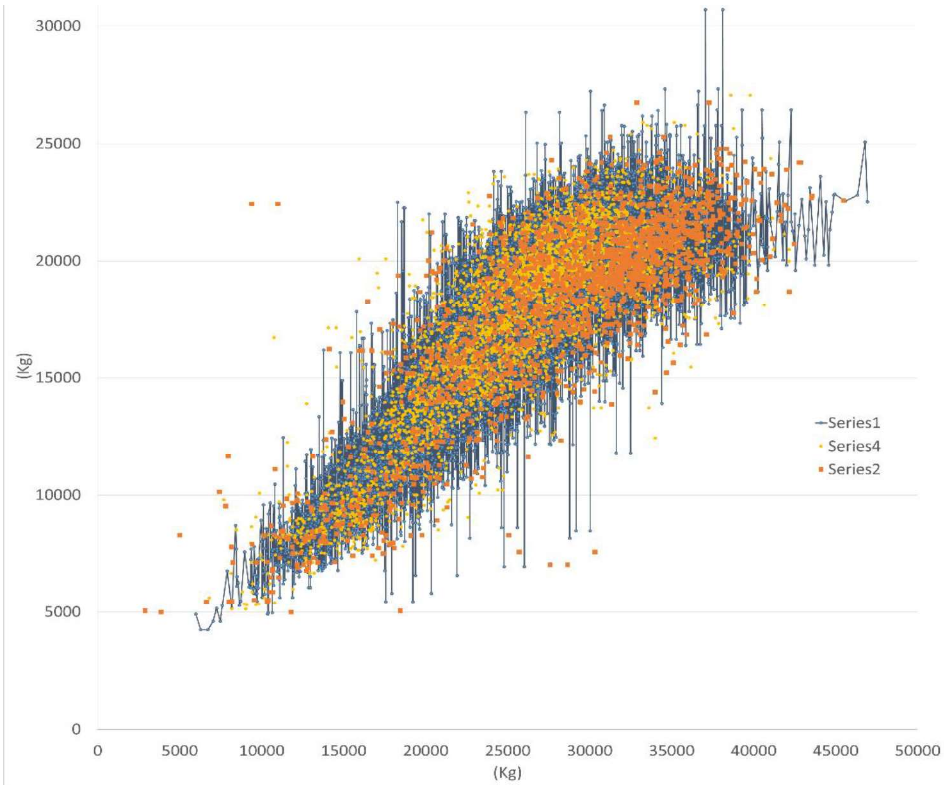

Figure 4 – some clusters of features extracted from load cell signal

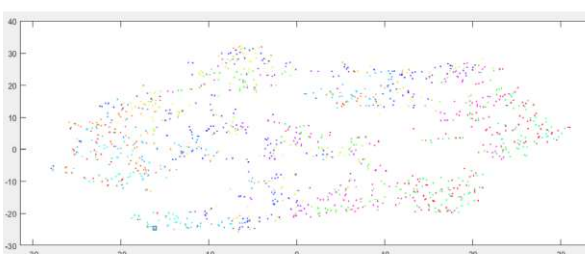

Figure 5 – T-SNE on load cell signal

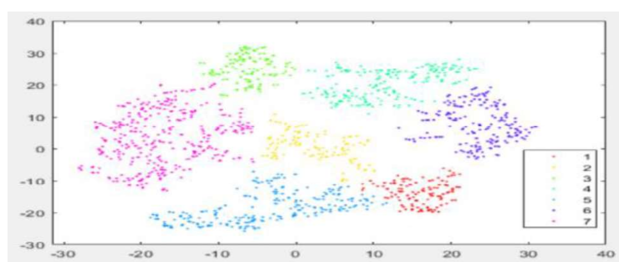

Figure 6 – clustering load cell signal

7. DNN construction for HS-WIM system

In a HS-WIM system, the relationship of speed, platform vibration, pavement roughness, pavement inclination, vehicle's suspension type and other factors is very complex and nonlinear. So, it is difficult to identify a function and specific mathematical expressions to represent static weight analytically. Therefore, in this study a DNN algorithm was proposed to predict the nonlinear relationships among those.

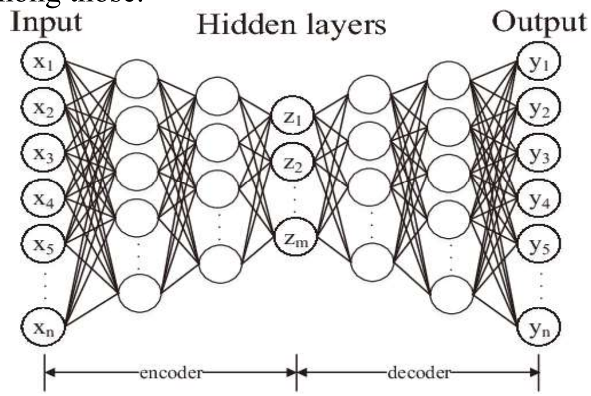

Figure 7 – Auto encoder architecture used for unsupervised learning of load cell signal

8. Data description

The training sets of labeled data (known reference static axle loads) were prepared from HS-WIM system installed in Ardestan in two lanes. More than 50000 random vehicles of 2-, 3-, 4-, 5-, and 6-axle trucks were weighted statically using reference instruments. Weighing instruments used to determine the static reference vehicle axle loads are OIML R76 certified. Therefore, reference static axle loads are all measured with less than ±1% error. So, we had a dataset of more than 300,000 axle weights with known referenced value. We used 70% of this data set for training of DNNs and 20% of data for test set and 10% for cross-validation of proposed DNN. Some of sample tests and reference axle weights are depicted in Table 1. Platform data (load cell signal) for all vehicles passing WIM system are recorded in text files. These files are analyzed off-line for training of DNN.

Table 1 – sample of referenced vehicle tests using static reference scale

				Static Weight (kg)			
Date and time	Speed (km/h)	Lane	Vehicle class	Group Axle1	Group Axle2	Group Axle3	Total Weight
20170814-125442	62	1	12	7200	12650	21890	41740
20170814-125449	57	1	13	5800	15600	20670	42070
20170814-125652	91	2	12	6780	12050	21550	40380
20170814-125709	78	1	13	6380	16070	20960	43410
20170814-125710	75	2	12	6910	11290	22430	40630
20170814-125829	74	2	7	7070	19920	0	26990
20170814-125838	70	3	12	7060	9950	22510	39520
20170814-125847	44	1	13	4350	14420	14900	33670
20170814-125853	52	1	13	6190	15310	14160	35660

9. Training of DNN

By using HS-WIM systems, the amount of each axle load, the total gross vehicle weight, and also the Equivalent Single Axle Load (ESAL) for each vehicle are estimated very accurately. Load cell signals for all 300,000 static axle weights are recorded then are pre-processed for feature extraction. After that data are sent to AE. Output from AE are sent to DNNs for training. Training process are repeated many times until the least square relative error is attained. The network is composed of five layers 23 nodes in input layer and 20 nodes in hidden layers and one node in output layer. Tangent hyperbolic function (tansig) was used in hidden layers and purelin function in output layer. In the proposed DNNs, Levenberg-Marquardt (lm) algorithm were used for training. Because the mean square error in lm algorithm decreases much more rapidly with time than other algorithms. Sometime training time would take half a day to be completed because of the big data sets we have. Each trained net is also tested on test sets and validation sets. Finally, the net with the least relative error (the highest accuracy) on train set, test set and validation set is chosen. Training results are depicted in Figure 8.

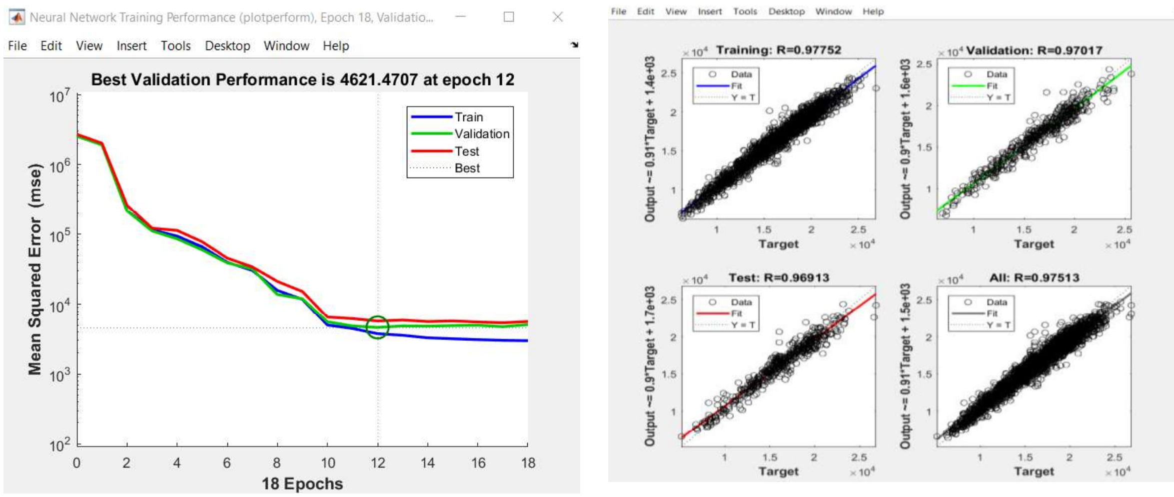

Figure 8 - regression results

10. Performance of DNN on HS-WIM and results

10.1 HS-WIM layout

Figure 9 shows layouts of the proposed HS-WIM systems and automatic number plate recognition system. This figure illustrates that there are two platforms installed next to each other with 7 cm space in each line; platform A1, platform B1 for fast lane (line 1) and platform A2, platform B2 for slow lane (line 2).

10.2 Field test results

Initial experiments with varying network depths showed that deep nets work better than shallow ones. Therefore, among different architectures of deep nets a DNN with 9 layers and tansig activation function has the highest accuracy in axle weight estimation. We trained two main collections: (1) high-speed load cell signals. (2) normal-speed load cell signals (shown in Figure 10). In high-speed cases, number of extracted features are less than normal-speed ones. But speed is not considered as an input to the DNN. The proposed technique was applied on 300,000 data of different random trucks from the traffic flow. All this data is from Ardestan HS-WIM site. Some of the test results are shown in Table 2. This table shows static reference weights, dynamic estimated weights and percentage of error between them. Performance of the trained DNN was calculated as mean square error (mse) on each data set. For the best results on the test and validation sets mse was 2.26 E7, 3.15 E7 respectively. This technique is working almost one year in Ardestan WIM site. Periodic tests are performed for this WIM system and all of the test results are within L (5) accuracy class and consequently eligible for direct enforcement. The suggested DNN technique is applied on other HS-WIM sites such as Delijan, Esfehan, Naeen and many other sites in the country. The proposed DNN technique would be fine-tuned for new WIM-installation sites using 200 test data. Thus, this approach is independent from road roughness and pavement conditions. The proposed WIM system is capable of recognizing driver behaviors such as rapid accelerating or decelerating. Using two platforms with 98 cm width (in direction of the traffic flow) made it possible to have complete tire contact-patch and tire load distribution. So, amount of damage caused by vehicle axle loads (ESAL) could be accurately calculated in this system. The results show that using two platforms in each lane increases accuracy of the axle weighing dramatically. It compensates for vehicle suspension vibrations and road unevenness as well. It seems that DNN is capable of managing big data efficiently from several load sensors. The suggested DNN is able to identify any underlying trends such as those due to spatial repeatability and to consider them in its estimate of static axle weight. The offered HS-WIM system is complied with OIML R134.

Figure 9 - HS-WIM system layouts

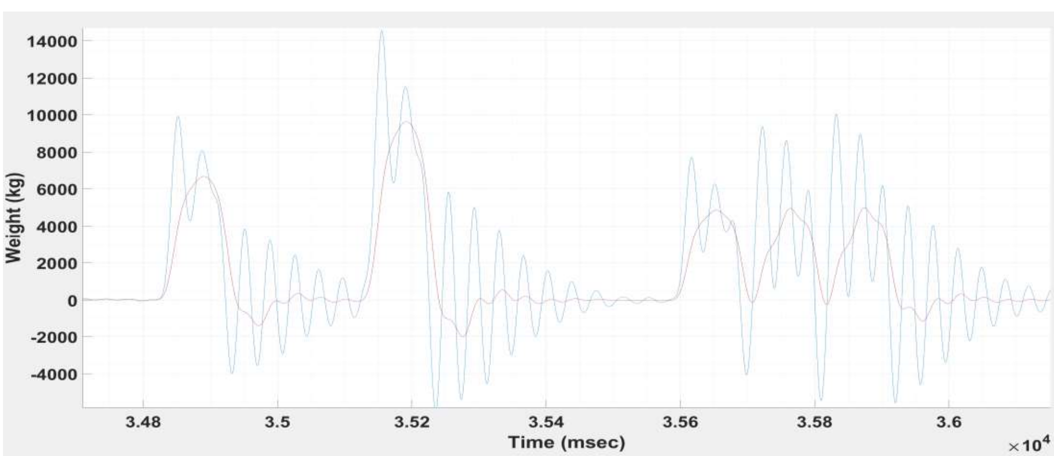

Figure 10 - some of typical load cell signals received from HS-WIM system that are inputs to AE and DNN

11. Conclusion

This research presents a deep neural network technique for dynamic vehicle weighing. The effectiveness of the proposed method is verified using five datasets from various HS-WIM sites in different places in Iran highways. These datasets contain more than 300,000 axles with known referenced weights. All these static weights are measured using control weighing instruments (static truck scales) which are certified according to OIML R76. Reference vehicles are various trucks randomly chosen from the traffic flow. All this labeled data is used for unsupervised and supervised learning processes. The results of these datasets shown that the proposed method is able to weigh axle loads of different trucks with L(5) accuracy. Every mechanical and electrical parts of HS-WIM system are interchangeable and the proposed DNN approach is able to identify any underlying trends and nonlinear relationships among characteristics of the system. Thus, the proposed method is the least dependent on road roughness and pavement conditions and L(5) accuracy class is obtainable with installing this WIM system anywhere other than current positions. The offered HS-WIM system is complied with OIML R134. In the proposed method, DNNs are trained using Levenberg-Marquardt (lm) algorithm. Because the mean square error in lm algorithm decreases much more rapidly with time than other algorithms.

Table 2 – some results from performance of the proposed DNN on HS-WIM: comparison of estimated axle weights and static weights are shown as relative error (% of error)

Speed (Km/h)	Vehicle class	Static Weight (kg)				Weight in Motion (kg)				% of error			
		GAX1	GAX2	GAX3	Total weight	GAX1	GAX2	GAX3	Total weight	GAX1	GAX2	GAX3	Total weight
68	13	5680	8680	9650	24010	5591	8514	9799	23904	-1.57	-1.91	1.54	-0.44
83	4	5660	9980	0	15640	5573	10640	0	16213	-1.54	6.61	0.00	3.66
78	13	5820	11720	11940	29480	5976	12360	12264	30600	2.68	5.46	2.71	3.80
75	4	5180	6420	0	11600	5322	6294	0	11616	2.74	-1.96	0.00	0.14
70	13	6370	18650	13360	38380	5935	20018	13197	39150	-6.83	7.34	-1.22	2.01
63	12	6370	12070	20510	38950	6263	11706	21110	39079	-1.68	-3.02	2.93	0.33
54	13	6620	17260	20240	44120	6342	17333	20325	44000	-4.20	0.42	0.42	-0.27
69	13	6540	14780	15690	37010	6593	14601	16755	37949	0.81	-1.21	6.79	2.54
72	7	6470	21960	0	28430	6890	21796	0	28686	6.49	-0.75	0.00	0.90
61	4	6380	13230	0	19610	6694	13394	0	20088	4.92	1.24	0.00	2.44

12. References

- Bahar, H., & Horrocks, D. (1998). Dynamic weight estimation using an artificial neural network. Artificial Intelligence in Engineering, 12(1-2), 135-139.
- Baladrón, C., Aguiar, J. M., Calavia, L., Carro, B., Sánchez-Esguevillas, A., & Hernández, L. (2012). Performance study of the application of artificial neural networks to the completion and prediction of data retrieved by underwater sensors. Sensors, 12(2), 1468-1481.
- Jain, A. K., & Dubes, R. C. (1988). Algorithms for clustering data.
- Jia, F., Lei, Y., Lin, J., Zhou, X., & Lu, N. (2016). Deep neural networks: A promising tool for fault characteristic mining and intelligent diagnosis of rotating machinery with massive data. Mechanical Systems and Signal Processing, 72, 303-315.
- Jiang, Q., Shen, X. Q., Cai, J. H., & Yao, Y. (2012). Application of RBF Neural Network in Dynamic Weighing. Paper presented at the Advanced Materials Research.
- Lin, H., Wang, L., Yu, J., Teng, Z., & Dai, H. (2015). Nonlinear Error Compensation for Load Cells Based on the Optimal Neural Network with an Augmented Lagrange Multiplier. IEEE Transactions on Instrumentation and Measurement, 64(11), 2850-2862.
- Wang, Y., & Flood, I. (2015). Comparison of Artificial Neural Networks and Support Vector Machines for Weigh-In-Motion Based Truck Type Classification. INFOCOMP 2015, 152.
- Zhi-feng, Z., & Chao-yang, W. (2015). Measuring Axle Weight of Moving Vehicle Based on Particle Swarm Optimization. Int. Journal of Research in Engineering and Science (IJRES), 2320-9356.