Improving measurements accuracy in weight-in-motion systems using dynamic neural networks

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Abstract

The work is devoted to the problem of weighing vehicles in motion as part of modern information technologies and automated intelligent systems of managing urban resources and infrastructure. The purpose of this work is to improve the measurements accuracy of weight-in-motion systems under heavy traffic conditions by developing an innovative weighting system based on dynamic neural networks as an integral part of intelligent urban infrastructure management systems, thereby contributing to the efficiency and sustainability of urban processes. Scientific novelty consists in the use of models in the form of time delay neural networks to process data from weighing sensors. The application of this approach allows increasing the accuracy of mass measurement in weight-in-motion systems in conditions of heavy traffic by taking into account the dynamic and nonlinear properties of the weighing process. The practical usefulness of the developed method lies in the development of new innovative weighing systems as part of modern information technologies and automated intelligent systems for managing urban resources and infrastructure. The application of dynamic neural networks for determining the mass of a vehicle in motion is a promising approach that allows to significantly increasing the speed of vehicle while maintaining the accuracy and reliability of mass determination.

Keywords

Weigh in motion, time delay neural network, nonlinear dynamic objects

1. Introduction

Nowadays, accurate and efficient weighing plays a key role in various fields such as transportation, logistics, construction and industry. Particularly important are weight-in-motion (WIM) systems, which allow controlling the weight of goods on transport routes without stopping them, thus ensuring smooth movement and optimization of transport processes [1].

Recently, WIM technologies have been increasingly used as part of modern information technologies and automated intelligent systems for managing urban resources and infrastructure. With the use of accurate and up-to-date information about moving cargoes today it is possible to solve such urgent problems as [2, 3]:

- controlling the load on road infrastructure and preventing its overloading to maintain road condition and ensure traffic safety;
- Optimizing transport routes to reduce travel time, fuel costs and the load on road infrastructure;
- control over the transportation of dangerous goods to ensure compliance with safety rules and regulations for their transportation;
- improving the environmental situation to reduce pollutant emissions and improve the environmental situation in the city. This is especially important in the context of modern urban development, when environmental problems are becoming more and more urgent.

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For example, WIM technologies play an important role in the tasks of intelligent urban management, helping to solve urgent problems related to transportation logistics, traffic safety and environmental sustainability.

In this context, the use of modern WIM technologies becomes a key element of intelligent urban management systems. Accurate data on the weight of vehicles and cargoes allow solving urgent tasks related to transportation logistics, road safety and environmental sustainability [4, 5]. However, existing WIM technologies are developed mainly for industrial and transportation and logistics enterprises and are not designed for operation in urban conditions. In this regard, the application of WIM technologies in urban areas under heavy traffic conditions faces certain difficulties [3, 6, 7]:

- Limited measurement speed, which may lead to errors when collecting load weight data.
- Limited measurement accuracy due to vibrations and other factors affecting the operation of sensors and equipment.

The purpose of this work is to improve the measurements accuracy of weight-in-motion systems under heavy traffic conditions by developing an innovative weighting system based on dynamic neural networks as an integral part of intelligent urban infrastructure management systems, thereby contributing to the efficiency and sustainability of urban processes.

2. Literature Review

Modern WIM systems based on several different implementations, depending on the principles of collecting information from the measuring sensors. Taking into account the peculiarities of operation in urban conditions, the most suitable of them are systems based on load sensors installed on the road surface [1, 2, 7] and systems based on resistive and deformation sensors, which register changes in the deformation of the road surface under the influence of transport [3, 8, 9].

The advantages of both approaches to mass measurement are high measurement accuracy, the ability to use in different weather conditions and for various types of transport, ease of maintenance and installation. Both WIM approaches use deterministic methods to filter, process, and calibrate signals to determine mass based on sensor readings. In this case, the accuracy of the weighing depends on a number of factors, such as the type of sensors used, the operating conditions, the quality of the calibration, and the data processing algorithms used.

The main disadvantage of this approach is the complexity of setting up algorithms for processing data received from sensors to measure mass in a wide range of changes in vehicle speed, traffic intensity, weather conditions, etc. [4, 9] This, in turn, gives rise to the problem of regular adjustment of algorithms and software updates. In cases where there is a large number of input parameters and a complex relationship between them and the output parameter that cannot be expressed analytically, approaches based on the use of machine learning methods, in particular, neural networks, demonstrate good results [10, 11]. In recent years, increasing attention has been paid to the use of neural networks to improve measurement accuracy in complex and changing environments. Dynamic neural networks, capable of adapting to changing input data and learning on the fly, offer significant advantages over traditional methods. These networks can take into account not only the current sensor values but also their temporal changes, allowing more accurate determination of the object`s weight in motion. Signal processing methods based on neural networks have a number of important advantages for solving the WIM problem [9]:

- detection of complex patterns, which makes it possible to model nonlinear dynamical systems, which include WIM systems;
- flexibility and adaptability to different types of data and changing conditions;
- the ability to generalize knowledge and apply it to new, previously unknown data.

Neural networks are a powerful tool for solving problems related to real-time data processing and analysis. In WIM systems, they can be used to improve measurement accuracy by taking into account multiple factors such as movement speed, changes in object position and dynamic loads. Thus, neural networks are a successful solution for improving the accuracy of WIM by taking into account the nonlinear and dynamic properties of the system, ensuring the reliability of the weighing process due to the adaptive properties of the system to data and operating conditions.

It should be noted that the idea of using neural networks in WIM systems is not new. There is significant work in this area [3, 9]. Convolutional neural networks (CNN) are used to identify hidden patterns and feature in the data, allowing for more accurate determination of the weight of an object moving on a platform [11, 12]. Feed Forward neural networks (FFNN) allow efficient processing of spatial data, providing high accuracy and reliability of measurements [12, 13].

However, related works are focused on the usage of neural networks of direct signal propagation, which do not take into account dynamic weighing processes [9], or on improving the quality of filtering and processing of signals from sensors. At the same time, the direction of using neural networks for modeling nonlinear dynamic properties of the WIM system is practically not developed [12, 13]. The approach based on the use of dynamic neural networks to the construction of WIM systems can be developed in several promising directions, allowing to significantly improve the accuracy, speed and reliability of measurements [14, 15].

Development of specialized neural network architectures: recurrent neural networks (RNNs) and their variants such as long short-term memory (LSTM), gated recurrent units (GRU), time delay neural networks (TDNN) [17, 18]. In the context of on-the-go weighting, they can use to predict weights based on a sequence of measurements, taking into account temporal dependencies and correlations, while having a significantly simplified architecture compared to FFNNs, CNNs. For more accurate processing of both temporal and spatial data, specialized neural network architectures in the form of combinations of neural networks such as convolutional (CNN) and recurrent (RNN) can be successfully applied. *Development of training algorithms with small amount of data*: for neural networks with specialized structure, it is much easier to develop algorithms that can effectively train on small data sets or with partial labeling, as well as to improve algorithms for noise filtering and elimination of artifacts caused by dynamic changes and external influences [19, 20].

Development of data preprocessing algorithms: for neural networks with specialized structure also, the task of noise filtering and removing artifacts caused by dynamic changes and external influences is simplified. *Increasing computational efficiency*: development and application of more compact and fast models based on recurrent neural networks allows building WIM systems on devices with limited computational resources, which reduces the cost of solutions, allows the realization of WIM systems within the IoT concept.

As a result of an analytical review of the current state the problem of improvement measurement accuracy of WIM, a promising direction based on the use of dynamic neural networks in the processing of data from weighing sensors has been identified. Using this approach, it is possible to ensure both high accuracy and speed of mass measurement in WIM systems in heavy traffic conditions.

3. Problem statement

A meaningful formulation of the problem of improving the accuracy of WIM systems in conditions of heavy traffic is to build a neural network model based on the data received from weighing sensors, reflecting the nonlinear and dynamic properties of the weighing process. Formally, the statement of the problem is as follows. Suppose a set of signals from a weighing sensor is given:

$$\mathrm{x}(t)=[x_1(t), x_2(t), x_n(t)], \tag{1}$$

and a set of labels (weighing results) corresponding to these signals:

$$\mathrm{y}=[y_1, y_2, y_n]. \tag{2}$$

Let's also have a training dataset

$$D=[(x_1(t), y_1), (x_2(t), y_2),\ldots, (x_n(t), y_n)], \tag{3}$$

where each pair $(x_i(t), y_i)$ is a description of the object $x_i(t)$ and the corresponding label y_i $(i=1,2,\ldots,n)$.

The task of improving the accuracy of WIM systems in conditions of heavy traffic is to build a dynamic neural network $F(\theta, D)$, where θ is a set of hyperparameters (set of factors), which are determined by the current requirements for the weighing system. At the same time, the $F(\theta, D)$ model should provide a minimum error between its output $\hat{y}_i$ and the experimental data y_i for $x_i(t)$ input:

$$F(\theta, D): arg\ min\ Q(y_i, \hat{y}),\ i=1,2,\ldots n, \tag{4}$$

where Q is the quality criterion of the model. The mean absolute error (*mae*) and mean square error (*mse*) can be used as a Q criterion [7, 9, 10]:

$$mae = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|, \tag{5}$$

$$mse = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2. \tag{6}$$

The Huber Loss function, which is a hybrid between *mae* and *mse*, has also been successfully applied to estimate regression models. Huber Loss calculates as follows [7]:

$$h = \begin{cases} \frac{1}{2n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2, |y_i - \hat{y}_i| \le \delta \\ \frac{1}{n}\sum_{i=1}^{n}\delta(|y_i - \hat{y}_i| - \delta/2), |y_i - \hat{y}_i| > \delta \end{cases}, \tag{7}$$

where δ is a hyperparameter that determines when to switch between *mae* and *mse*.

If condition (4) is satisfied, we get a model $F(\theta, D)$ that most accurately maps the set of $x(t)$ signals to the set of y labels. Thus, the problem of improving the accuracy of WIM in conditions of heavy traffic lies in the formation of a dataset based on expression (3) and training on its basis a dynamic neural network $F(\theta, D)$ that satisfies condition (4).

4. A Method for Improving Weighing Accuracy Using Neural Network Models

4.1. Time delay neural networks

Today, there are several common methods for modeling nonlinear dynamical objects using NM: dynamic neurospatial mapping (Dynamic Neuro-SM), dynamic neural networks of the veneer type (Wiener-type DNN) and neural networks with time delays (TDNN). Among these variants of nonlinear dynamic neural network models, TDNN is the most common structure, consisting of several layers with direct signal propagation [11, 12]. Such models can improve the accuracy of WIM systems by taking into account the dynamic behavior of a system with nonlinear characteristics [10–12], as well as adapting to data and external conditions. Due to its simplicity and versatility in modeling nonlinear dynamic objects, TDNNs have become the most widespread. There are many structures of TDNN neural networks, differing in the number of hidden layers, activation functions, and topology. To simplify the description of the TDNN-based model, the most commonly used TDNN structure, consisting of three layers: input, hidden, and output, is considered further [13]. In this structure, the input layer TDNN includes M neurons, the hidden layer includes K neurons, the output layer includes 1 neuron. Fig. 1 shows the TDNN architecture as a three-layer network with direct signal propagation with M inputs, a hidden layer with K neurons, and one output neuron [14, 15].

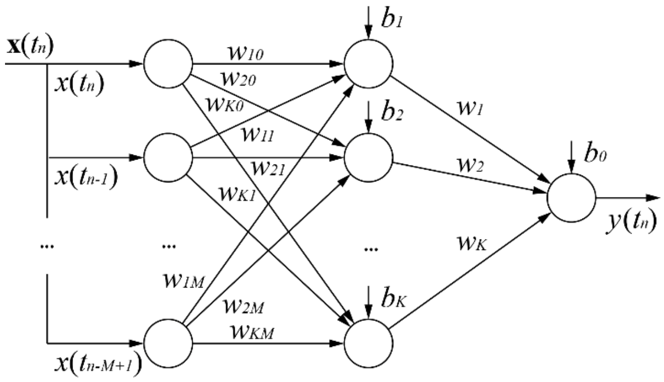

Figure 1: TDNN architecture as a three-layer network with direct signal propagation

The use of this structure gives a less complex expression for the NN output compared to other structures. The signal $y(t_n)$ on the output layer at time t_n depends on the values of the input signal $x(t_n)$ and is determined by the expression [15, 16]:

$$y(t_n) = b_0 + S_0 \sum_{i=1}^{K} w_i S_i \left[b_i + \sum_{j=1}^{M} w_{i,j} x(t_{n-j}) \right]. \tag{8}$$

where b_0, b_i are the displacements of the neurons of the original and hidden layers, respectively; S_0, S_i – functions of activation of neurons of the original and hidden layers, respectively; w_i, w_i, j – are the weighting coefficients of the neurons of the original and hidden layers, respectively.

4.2. Definition of TDNN Structure

The layers present in the network are: input (receives input), output (forms the final result), and hidden (processes data from the input layer).

Determining the size of the model memory. The input layer in the defined TDNN structure includes M neurons, where M is the memory length of the object model. The number of neurons M is chosen in such a way as to best reflect the dynamic properties of the object. The size of the input layer of a neural network M when modeling a dynamic object depends on many factors, including the amount and type of input data that describe the state of the object and its environment. In the case when information about the transient process is available, the determination of the model memory size comes down to the determination of its duration. This value implies taking into account the temporal dynamics of the input data and the state of the model. Thus, as the memory size of the system (the number of neurons in the neural network input layer) is taken as the number of time steps or the number of previous states that the model must take into account to accurately predict the current state.

The following algorithm quantifies the memory size of the system, which will be useful for determining the structure of the neural network model.

1. Determination of the time sampling step Δt that will be used to discretize the data. It is important to choose a step small enough to capture the dynamics of the system, but not too small so as not to excessively increase the amount of data.
2. Transient data acquisition: representation of input signals in discrete form x(t):

$$\mathrm{x}(t)=[x_1(i\Delta t), x_2(i\Delta t), x_n(i\Delta t)], \tag{9}$$

where $i=1,2,\ldots n$, $n\Delta t$ – signal observation time.

3. Determining the transient time: obtaining the time interval T_p, during which the system response enters and remains within a certain range around the steady-state value for the first time (in practice, 1-5% of the steady-state value).

This time corresponds to the moment when the system stops “remembering” its initial conditions and stabilizes.

4. Determining the memory size: obtaining the number n of neurons in the neural network input layer:

$$M= T_p/\Delta t. \tag{10}$$

Determining the size of the hidden layer of the model. The hidden layer includes K neurons with a nonlinear activation function. The number of K neurons is chosen in such a way as to best reflect the nonlinear properties of the object.

The output layer of the network in the simulation problem is equal to the number of outputs of the weighing system and is equal to one. To reflect the dynamic characteristics of the system, the output signal of the network $y(t_n)$ at time t_n must depend not only on the input signal $x(t_n)$ at a given time, but also on the input signals operating at previous moments of time t_{n-1}, t_{n-2}, ..., t_0, $t_n=n\Delta t$, $n=1, 2, \ldots, M$. In this case, a neural network with time delays must receive specially prepared input data:

$$\mathrm{x}(t_n)=[x(t_n), x(t_{n-1}), \ldots , x(t_{n-M-1})]. \tag{11}$$

or in matrix form:

$$x_n, x_{n-1}, \ldots , x_{n-M+1} \tag{12}$$

$$x_{n-1}, x_{n-2}, \dots, x_{n-M}$$

$$\dots$$

$$x_M, x_{M-1}, \dots, x_1$$

4.3. TDNN Construction Method for Estimating the Mass of Vehicles in Motion

The method of constructing a TDNN model for estimating the mass of moving vehicles is as follows.

Inputs: Data coming from the sensors of the WIM system, such as pressure or strain signals, road conditions.

Output: Real-time estimation of the weight of the cargo carried by the vehicle based on the analysis of the input data using a trained neural network.

Quality assessment metrics: root mean square error.

Algorithm of improving the accuracy of WIM systems using time delay neural network:

1. Formation of a dataset D based on expression (3) using data from sensors x(t) and labels y (weights of test objects).
2. Determination of the time sampling step Δt that will be used to discretize the data; formation of a discrete dataset D_d=[($x_1(i\Delta t)$, y_1), ($x_2(i\Delta t)$, y_2),..., ($x_n(i\Delta t)$, y_n)].
3. Preprocessing the data D_d: clean the data, remove noise and outliers. Normalize x(t) to ensure uniformity of value ranges.
4. Determination of the three-layer structure of the neural network $F(\theta, D_d)$: initialization of the number of input layer neurons M to display the dynamic properties of the system; the number of hidden layer neurons K to represent the nonlinear properties of the system [15, 16].
5. Training a neural network on a prepared dataset D_d using the backpropagation method.
6. Estimating the quality of the model on a test dataset using a criterion in the form of a mean square error.

The block diagram of TDNN is shown in Fig. 2. In this figure, the value None in the data dimensionality vector means the variable number of rows in the dataset.

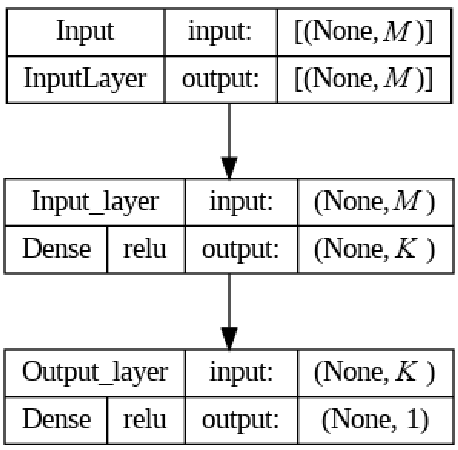

Figure 2: Structure diagram of the TDNN with M inputs and K hidden neurons

5. Experimental setup

Testing of the proposed method for improving the accuracy of WIM is carried out using an imitation model, with the help of which the training dataset is formed. The simulation model of the WIM system designed to collect statistical data on the signals from piezo sensors about the mass of vehicles received during their movement. Creating a simulation model of the WIM system in the form of a stand in miniature allows visualizing and testing the system operation in a controlled environment.

Such a model can be used for preliminary testing of hardware and software. The main components and stages of creating a simulation model of the WIM system:

1. Weight sensors installed in the road surface, measuring the weight of vehicle axles as they pass: x(*t*) signals.
2. A database where the collected data from the sensors x(*t*) and the actual vehicle weight y are accumulated.
3. Software that collects data from the sensors and stores them in the database.

Based on the simulation model of the WIM system, a set of signals x(*t*) from the piezo sensors of the WIM system for different loads and different vehicle speeds, and a set of labels y in the form of exact vehicle mass values for each experiment are obtained.

A three-layer neural network is used to build a neural network model of the WIM system. The input layer size is taken as M=15 (at Δt=0.05 s) to represent the dynamic properties of the system; the hidden layer size K=50 to represent the nonlinear properties of the system.

As a result, a three-layer neural network was created and trained. The input signal x(*t*) is fed to M neurons of the input layer.

The hidden layer consists of K neurons. The output layer consists of one neuron with a linear activation function. The TDNN was trained using data collected using a simulation model of the WIM system.

The Levenberg-Marquadt algorithm was used for training. The training time of the neural network averaged 25-35 minutes on a dataset of 2000 vehicle passages, which is acceptable for practical applications.

In this paper, the obtained experimental data was processed by two models: using Kalman filtering and using a TDNN.

The dependence of the accuracy of weighing results (metrics *mse* and *Huber loss*) on vehicle speed investigated for both models is shown in Fig. 3 and Fig. 4 accordingly.

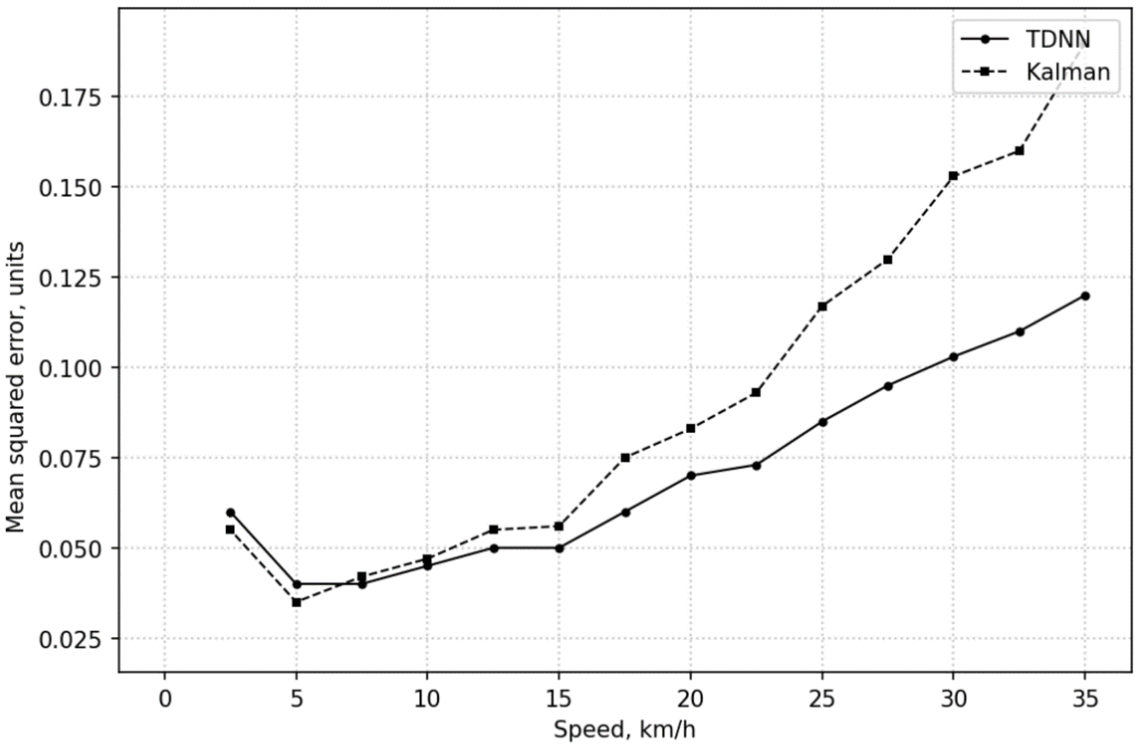

Figure 3: Comparison of weighing accuracy (metric *mse*) using Kalman filtering and a neural network with time delays

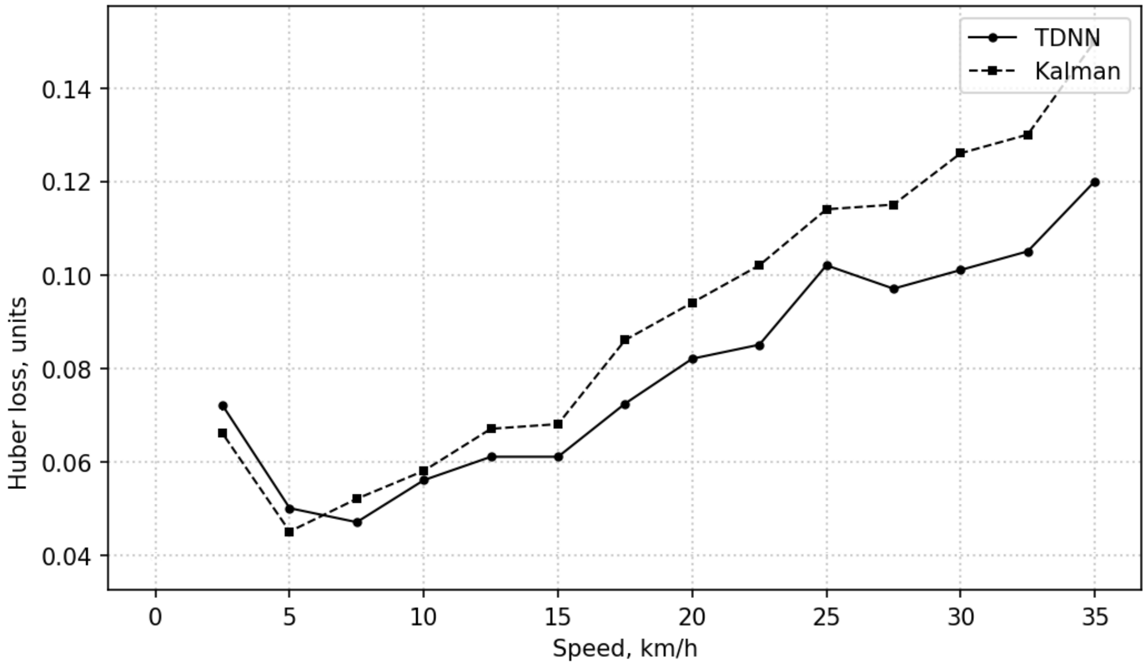

Figure 4: Comparison of weighing accuracy (metric *Huber loss*) using Kalman filtering and a neural network with time delays

The Keras software tool (keras.io) used to create a neural network. It is one of the key Python libraries for efficient API organization when modeling neural networks of any complexity. The library is most effective when building small networks with a sequential structure, where layers follow each other, as well as with one input and one output layer. Although it is possible to model more complex neural network structures with feedbacks, multiple inputs and outputs. To build feedforward networks in Keras, we can use any number of successive layers of predefined types: Input, Dense and Activation. The library has a ready set of loss functions and optimization algorithms that allow us to quickly train the model and avoid local minima if possible.

6. Results

The results shown in Fig. 3 demonstrates the advantages of using the proposed WIM method based on a neural network with time delays compared to the method based on the use of Kalman filtering at traffic speeds from 15 km/h to 11% and from 25 km/h to 16%. At speeds of up to 15 km/h, the accuracy of both methods is comparable. At the same time, the accuracy of measurements in traditional methods that use static models and linear algorithms to determine the weight of vehicles demonstrates a root-mean-square error (rmse) [7, 10] at the level of 12-15% of the true weight. The application of dynamic neural networks reduced the RMS error to 10-12%.

Dynamic neural networks showed a high ability to adapt to different road conditions and vehicle types. Experiments were conducted under varying traffic speeds, different road conditions. The neural networks successfully trained on data obtained under different conditions and showed more stable measurement accuracy when these conditions changed. After training, the model demonstrated high performance in real-time data processing, providing fast and accurate estimation of vehicle weights.

As a result of the experiment, it was found that the accuracy of weight determination was significantly influenced by the speed of vehicles: Dynamic neural networks showed the ability to better adapt to changes in vehicle speed, which is critical for measurement accuracy.

Advantages of the proposed model. The advantages of the proposed approach for weight determination in WIM systems are high measurement accuracy, ability to adapt to changing operating conditions, and high speed of data processing and prediction generation.

Disadvantages of the proposed model. As limitations of the application of dynamic neural networks in WIM systems is the dependence of the model on the quality and amount of data used for training [20–22]. Insufficient data or low quality data can significantly reduce the accuracy of the measurements.

In addition, to maintain high accuracy, the model needs regular updating and calibration, which may require additional resources and effort. This problem can be partially solved by using real-time reinforcement learning algorithms.

Recommendations for practical application. Integration of dynamic neural networks into existing WIM systems to improve measurement accuracy can be accomplished through software upgrades and additional sensor calibration to ensure high accuracy and reliability [23, 24].

7. Conclusions

As a result of the work, the problem of increasing the accuracy of measurements in WIM systems under heavy traffic conditions has been successfully solved, and a method of processing the initial data from sensors based on machine learning model in the form of TDNN has been proposed. The developed method allows building neural network model of WIM processes, taking into account their nonlinear and dynamic characteristics, which makes it possible to increase the accuracy of weight estimation of railroad cars and motor vehicles.

The method was tested on a simulation model of the WIM process. Compared to traditional methods using static models and linear algorithms, dynamic neural networks showed a significant improvement in accuracy. Experimental data showed a reduction of mean squire error up to 16% compared to the traditional method used in WIM systems based on Kalman filters, which confirms the effectiveness of the proposed approach. The study established the area of effective use of the proposed method in the range of speeds from 15 to 35 km/h.

The dynamic neural networks underlying the proposed WIM method are able to adapt to various factors affecting the measurements, such as vehicle trajectory, road surface condition, changes in vehicle characteristics, etc. This makes them particularly useful for long-term use in real-world applications. At the same time, the trained neural network in operation mode allows real-time data processing that is as fast as traditional weighting methods in processing sensory information, which is crucial for WIM systems.

The research has opened new opportunities for further improvement of WIM systems. Thus, research aimed at improving the architecture of neural networks is promising: the use of RNN and LSTM, which can better account for temporal dependencies and vehicle dynamics with less complexity of the network. Also of interest is the use of hybrid models that combin neural networks with traditional data processing methods to improve the accuracy and reliability of measurements; the study of additional parameters such as pavement vibration data, atmospheric conditions, and vehicle condition information that can be included in the model to improve the accuracy, and reliability of measurements.

In conclusion, the use of dynamic neural networks to determine the weight of vehicles in motionis is a promising approach that can allow to significantly increase the speed of vehicle movement while maintaining the accuracy and reliability of determining their weight. This, in turn, makes it possible to obtain prompt and accurate information on traffic flows and contributes to more efficient management of transportation infrastructure and cargo flows.

The obtained results can serve as a basis for the development of new innovative weighing systems as part of modern information technologies and automated intelligent systems for managing urban resources and infrastructure.

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