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Prediction of Traffic Accidents by Using Neural Network

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ABSTRACT

The prediction of traffic accidents in urban networks is one of the key future theme in the areas of traffic control and navigation. Early identification of the risk of a traffic accident can lead to an increase in the safety and smoothness of road transport. Neural networks belong to the expert methods for modeling of complex systems. The issue of their use in the transport sector is scientifically quite progressive. The article describes the design of prediction model based on available traffic data from town Uherské Hradiště. Traffic data was collected from many sources, e.g. junction detectors, meteorological stations or traffic accident portal. Appropriate parameters for the model were selected from the traffic data. The model was then tested on a 2-month data sample. The aim of the article is to confirm the suitability of using neural networks to predict traffic accidents.

KEYWORDS: traffic accidents, predition, neural networks

1. Introduction

With the increasing degree of automobilism in larger cities, the demand for deploying of intelligent transport systems is rising. The prediction of traffic variables is one of the key future topics in the areas of traffic control and navigation. Timely anticipation of traffic accidents is important for strategic management of larger urban areas in order to increase traffic safety and fluency, reduce emissions and reduce the overall economic costs of transport. In addition, timely accident prediction can help the drivers themselves to reduce the risk of additional traffic excesses and optimize the use of transport capacity.

This article describes the design of prediction model based on available traffic data from town Uherské Hradiště. Traffic data was collected from many sources, e.g. junction detectors, meteorological stations or traffic accident portal. Appropriate parameters for the model were selected from the traffic data. The model was then tested on a 2-month data sample.

2. State-of-the-art

Compared to classical analysis, the advantage of neural networks for predicting time series is the ability to learn from measured data and the ability to detect hidden non-linear dependencies. The disadvantage, on the contrary, lies in the fact that it is not possible to predict the magnitude of the forecast error or to determine the confidence interval. In general, the main task is to find the optimal system model. There are two ways to do it:

- Deductive method - First, the general model is selected and then it adapts to the desired behavior during learning, which means that the model of the system that is being searched is created by setting the coefficients. Most neural networks are based on this principle. Even in the case of the problem of prediction of traffic surpluses, the deductive way seems more effective.
- Inductive method - At first, there are only a few basic building units, and only during the learning phase is an effort to create a suitable model that best suits the desired behavior.

The use of neural networks for prediction in time series is also solved by many authors in their publications. According to sources

Mr. Biskup deals with the possibilities of neural networks [1] in his dissertation work.

Mr. Obitko describes [2] on his website the possibilities of neural networks and genetic algorithms in an illustrative form.

The theme of using neural networks for transport prediction is a fairly new and modern theme, most of the available resources are from the last few years:

- The article [3] focuses on prediction of traffic accidents on a certain section of the expressway in Malaysia where selected input parameters for the prediction model were the site of the accident, the reported cause of the accident, the condition of the road surface, the lighting, the type of collision, the time of the accident, and shows that the prediction model can determine the most frequent accidents in the area for the traffic data sample and can be more accurate than the conventional statistical models.
- The article [4] is then focused on predicting the severity of traffic accidents based on a historical data model from the Abu Dhabi region of 2007-13, and the developed neural network model has again shown a relatively high accuracy of 74.6% compared to statistical models showing accuracy 59, 5%.
- The article [5] deals with the use of neural networks for prediction of traffic accidents in Jordan.

3. Assessed locality

The Author Team, in cooperation with the city, continues in its chosen location for its previous work on traffic surveys [6], traffic data collection [7] and traffic control [8].

The city of Uherské Hradiště is located in the Zlín Region on the banks of the Morava River in the South-East of the Czech Republic. It is one of the largest cities in that region and along with the towns of Kunovice and Staré Město u Uherského Hradiště it forms an agglomeration with 38 000 inhabitants. Uherské Hradiště has a diametrical road network with a city bypass that appears to be insufficient due to the location of the city and the adjacent cities. A through-way of the road I/55 goes through the city as well as the original through-way of the road I/50, which is now running along the city bypass.

There are 8 light-crossed intersections in the area. All intersections have the most straight ahead directions in the main routes (directly), while the crossroad Velehradská třída x Sokolovská also shows high values of traffic intensity on the lateral arms, especially on the eastern (direction from Zlín). The map of the surveyed area is available in Fig. 1.

The predominant part of the traffic flow is passenger cars, however, given the absection of the by-pass in the north-south (and south-north) direction, there is a considerable proportion of freight traffic. The city is also suitable for cyclists, as well as the transport infrastructure.

From the point of view of the availability of transport data sources, the data from junctions containing intensities and occupancy were used for the project. The speed of transport vehicles is gained through the RODOS project from floating vehicles in the network. Furthermore, data from the meteorological station in the Old Town near Uherské Hradiště is available for the project. Last but not least, historical accident data provided by the Czech Police are available.

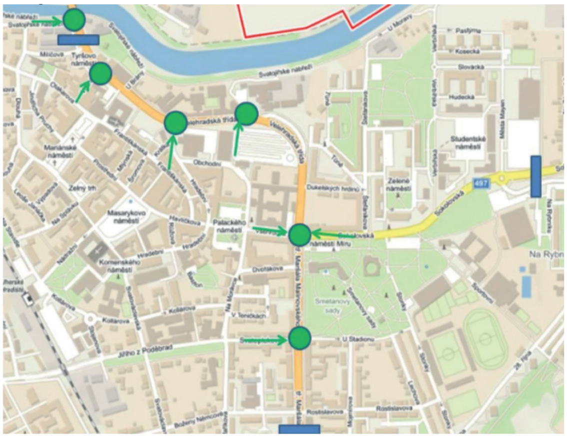

Fig. 1 Map of the surveyed area [10]

4. Analysis of available data

In order to use data for modeling and subsequent evaluation, the general way of working with data is to be observed:

- Data collection (selecting the appropriate data sources described in the above chapter)
- Data retrieval (use of appropriate SW to read the files in which the data is stored)
- Data filtering (removal of unnecessary values for the purpose of the project, eg, values that are in locations outside the selected locations)
- Data checking (verifying whether the data is complete or whether there are incomplete or missing entries)
- Data correction (loading method with missing records, see below):
  - Excluding all missing or incomplete records from further processing
  - Replace (imputation) of missing data and then process complete data. Here, many ways of imputing missing records can be chosen: deductive imputation, substitution with average value, substitution by group (conditional) average, median, or multidimensional imputation (regression imputation, hot-deck imputation, random closet algorithm).
  - Incomplete data processing by special methods

Below is a specific description of the process of checking the individual data sources, including the method of data correction:

The data relation to occupancy and intensity records at 7 junctions in Uherské Hradiště. Within each intersection, data is broken down by individual detectors relevant to a particular junction. An EM (Expectation-Maximization) algorithm was used to estimate the missing data for the occupancy and intensity records from Uherské Hradiště. This is a popular iterative method that is used to find a maximum assurance estimate from a set of data that is incomplete or has missing values. Each iteration consists of two parts. In step E (expectation) we create the expectation of the logarithmized assurance of the complete data, which is conditional on the observed data and also on the current estimation of the parameter under consideration. Step M (Maximization) then searches for a new estimate that will maximize the function obtained in the previous section and is then used in the next iteration in step E.

In the case of metrological data, Predictive Average Matching (PMM) was used to predict the missing values, partly based on regression of missing values. For each imputation variable and missing value case, a value is predicted (according to a defined regression model). Subsequently, for this case (for each case with missing values for the imputed variable), several cases are selected for which the value of the imputed variable is observed and at the same time these selected cases of observed values are close to the predicted value from the regression model. Eventually, one of these "donor" cases is chosen, the observed value being added to the current imputed case.

5. Prediction model using neural networks

Used method

In the design was used multilayer neural network (Multilayer perception) described for example in [9], a network with one or more hidden layers of neurons located between the input and output layers. The neuron input layer sends its input to all of the inner layer neurons. The inner layer outputs are fed to the inputs of each higher layer neuron and are multiplied by the respective weights.

The multilayer neural network, unlike the single-layer potential, also has to deal with nonlinear problems, learning such a network is much more complicated. There is no fixed relationship to determine the number of multilayer neural network layers and the number of neurons in these layers; the topology of the neural network must always be determined experimentally. However, there are a few rules and recommendations that can make it easier to choose the topology of a neural network.

To solve most problems, a neural network with just one inner layer is almost always enough. Topology with two inner layers is often needed when the neural network is learning a discontinuous function. There is no theoretical reason for using more than two inner layers. Practical experiments, however, show that the problem will be more efficiently solved by using a neural network with multiple layers of fewer neurons than using a smaller number of layers with an impractically large number of neurons. After selecting the number of layers, you must select the number of neurons in these layers. Choosing the correct number of neurons is very important. Using a small number of neurons, the neural network will not have enough capacity to learn the problem. Conversely, when too many neurons are used, there is a significant prolongation of the learning period, and there may also be a problem called the neuronal network overfitting.

Neural network overfitting occurs when this network has too many resources to process information. It is a condition where the neural network learns unduly accurately a set of training data, including its random errors or noise, thereby losing its generalization capability. Conversely, the retrieved neural network achieves excellent results with training data, when working with a test set of data, or when used in a real-world application, but the results are unwanted.

The number of neurons is usually determined experimentally, for example, by initially choosing the number of neurons that is too small.

Next, the method of calculating a network error is determined, a criterion determining how well a neural network is taught. Then there is a gradual increase in neuron counts, re-training and network testing, until the network error falls below an acceptable limit or until no improvement is achieved.

The neural network uses the backpropagation learning algorithm, the most widely used neural network learning algorithm (approximately 80% of all applications).

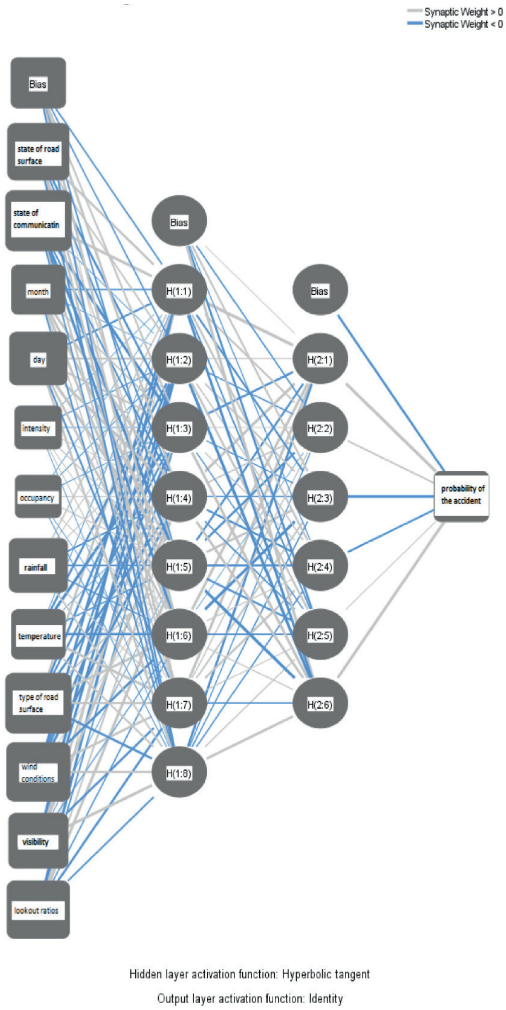

Fig. 2 Proposed neural network [own study]

Figure 2 shows a specific neural network model for a test sample. The input layer of the model contains 12 input variables to create a model that is able to predict the probability of an accident in the output layer in the best way. The neural network contains two hidden layers. These are the layers located between the input data layer and the output variable layer where the neurons capturing a plurality of weighted inputs produce the output through the activation function. Elements of a neural network containing an activation function are called artificial neurons.

The first hidden layer contains 8 of these neurons, the second layer contains 6. The hidden layers also contain the Bias unit. The bias is an 'extra neuron' added to each hidden layer, the Bias in one hidden layer being unrelated to the elements in the previous hidden layer. The Bias function is to shift the activation function. The function of the hyberbolic tangent was chosen as the activation function that contained neuronal neurons in the neuronal network.

The paths between the individual input variables, the neurons in the individual layers and the output are called synapses. The blue synapse signifies strong connections, ie, connections that significantly contribute to the predictive power of the model. The gray synapse signifies weak connections with little influence on the predictive power of the model. The model was trained and then tested on a 194024- file data sample. (essentially 2-3 months of available traffic engineering data, while 70.1% of the cases were used to train the used model or its production, and 29.9% of the cases were used to test the generated and used algorithm.

6. Test results for the data simple

From Fig. 3 below, we can see for example the representation of the accuracy of prediction of the probability of the occurrence of traffic excess II. type using the box graph. The x axis is the values of the input variable, ie the probability of an accident based on the input data sample. The y-axis is then values predicted by the neural network.

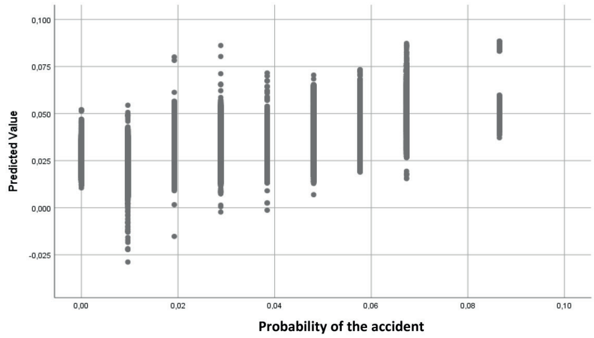

Fig. 3. Illustration of the accuracy of the prediction of the probability of traffic accidents [own study]

Fig. 4 below gives a graphical representation of the importance of the individual input variables for the predictive power of the model. It can be seen from the illustration with the parameters of road surface condition, communication state, weather conditions and look-out ratios have had the greatest influence on the predictive power of the model, while the influence of the detector, occupancy and intensity has had little influence on the predictive power of the model.

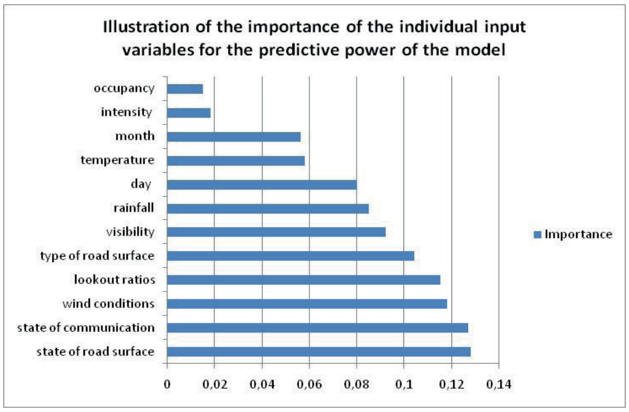

Fig. 4. Illustration of the importance of the effects on traffic accidents [own study]

7. Conclusion

Below are the main activities completed this year:

- Parameters analysis with impacts on traffic accidents was carried out.
- A search of projects was carried out which dealt with the prediction of traffic excesses using the tool of neural networks.
- Extensive analysis of available data sources and usability of available engineering data for the design of the mathematical model.
- Inputs and outputs of the mathematical model of the neural network were proposed. This network was then trained and tested on a data sample from Uherské Hradiště.

The mathematical model of the neural network has proven usable. In the future, then, it is supposed to continue working through the following steps.

- Implementation of the proposed mathematical model into software.
- Implementation of the proposed algorithm from the previous stage into the transport application. The algorithm will be implemented using available data.
- Testing the proposed prediction module on the bigger data sample.
- Integration of the proposed module into the control platform.

Prediction of traffic excesses II. type (traffic accidents) with the use of neural networks is a topical issue that can be solved in many parts of the world, from the available and other similarly focused articles. The potential is represented by the prediction of transport I. type (traffic jams) through neural networks, to which no relevant sources of research results were found in the search, and it can therefore be assumed that this problem is not explored more deeply.

Bibliography

[1] BISKUP R.: Možnosti neuronových sítí, disertační práce, Česká zemědělská univerzita, Praha, 2009

[2] OBITKO M.: Interactive tutorials, mainly from the area of artificial intelligence. [online], 1999 [date of access: 22.01. 2019]. Dostupné z URL: <http://www.obitko.com/tutorials/>.

[3] SAMEEN M., PRADHAN B.: Severity Prediction of Traffic Accidents with Recurrent Neural Networks. Applied Sciences [online], 7(6) [date of access: 22.01.2019]. DOI: 10.3390/app7060476. ISSN 2076-3417. Dostupné z: http://www.mdpi.com/2076-3417/7/6/476, 2017

[4] ALKHEDER S., TAAMNEH M., TAAMNEH S.: Severity Prediction of Traffic Accident Using an Artificial Neural Network. Journal of Forecasting [online], 36(1), 100-108 [date of access: 22.01.2019]. DOI: 10.1002/for.2425. ISSN 02776693. Dostupné z: http://doi.wiley.com/10.1002/for.2425, 2017

[5] JABAR Y., RABABAA M.: Neural Technique for Predicting Traffic Accidents in Jordan. journal of american science. 9. 347-358, 2013

[6] RŮŽIČKA J., et al.: Implementace systémů řízení a senzorických sítí ve městě; Silniční obzor, 2018(5), 138-141. ISSN 0322-7154, 2018

[7] RUZICKA J., et al.: Methods of traffic surveys in cities for comparison of traffic control systems — A case study. In: 2018 Smart City Symposium Prague (SCSP) [online]. IEEE, 2018, s. 1-6 [date of access: 22.01.2019]. DOI: 10.1109/SCSP.2018.8402666. ISBN 978-1-5386-5017-2. Dostupné z: https://ieeexplore.ieee.org/document/8402666/, 2018

[8] BOYARKIN I., et al.: Implementation of new adaptive control algorithms in the defined urban area. In: 2018 19th International Carpathian Control Conference (ICCC) [online]. IEEE, 2018 s. 608-612 [date of access: 22.01.2019]. DOI: 10.1109/CarpathianCC.2018.8399702. ISBN 978-1-5386-4762-2. Dostupné z: https://ieeexplore.ieee.org/document/8399702/, 2018

[9] GHAFARI E., et al.:Full Paper-BMC 2012-EG-04-1 revEJ, 2014

[10] mapy.cz. [Online] [date of access: 2.10.2018] https://mapy.cz.