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# Innovative neuro-fuzzy system of smart transport infrastructure for road traffic safety

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# Innovative neuro-fuzzy system of smart transport infrastructure for road traffic safety

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**Abstract**. The proposed study describes applying of neural network and fuzzy logic in transport control for safety improvement by evaluation of accidents' risk by intelligent infrastructure devices. Risk evaluation is made by following multiple-criteria: danger, changeability and influence of changes for risk increasing. Neuro-fuzzy algorithms are described and proposed for task solution. The novelty of the proposed system is proved by deep analysis of known studies in the field. The structure of neuro-fuzzy system for risk evaluation and mathematical model is described in the paper. The simulation model of the intelligent devices for transport infrastructure is proposed to simulate different situations, assess the risks and propose the possible actions for infrastructure or vehicles to minimize the risk of possible accidents.

## 1. Introduction

The amount of used transport vehicles is growing very speedily. This causes the bigger amount of road accidents. That is why transportation safety is one of the most studied subjects nowadays. Road accidents can lead to terrible consequences. Safety is one of the first priority tasks in transport domain. A lot of road accidents and crashes caused by driver factor. Driver factor depends on the mood, physical and psychical condition of the driver [1]. A lot of scientists are interested in inventing the intelligent system, which could reduce the human factor by smart analyzing the situation on the road, making the decisions to avoid dangerous situations and transmitting the solution from the infrastructure to the vehicles [10].

Different researches about road traffic safety are made. Neural network is proposed for the traffic sign recognition process [2], for the road surface traffic sign detection [3], risk evaluation [4] etc. Simple fuzzy severity estimation model has a comparable performance to more complicated systems such as the CoTEC (CoOperative Traffic congestion detECtion) [9]. That proves the actuality of the chosen topic.

In the previous works, the system and the algorithm for anti-collision system reducing human factor has been developed and tested [5]. Also intelligent transport safety system was investigated and designed by paper authors [6]. This research is a development of the innovative neuro-fuzzy system of smart transport infrastructure.

The main advantage of the proposed system is that system is using real-time data makes the decision about speed change instantly.

## 2. Problem formulation
The main purpose of the proposed system is to evaluate the collision possibility and to make a decision about speed change of the vehicles.

The goal of current research is to develop the system for risk evaluation.

The following tasks are defined and solved:

1) to define the structure and functions of the system,
2) to develop the mathematical model and multiple criteria target function for collision possibility minimization,
3) to develop the adaptive algorithm of the system functions,
4) to develop the computer model and simulate the developed algorithm. To compare results before and after neural network training process,
5) to implement the model and the algorithm for microcontroller based embedded devices as a functional prototype of the system.

## 3. Neuro-fuzzy system model
In this paper, neuro-fuzzy control proposed to be taken as intelligent control method. While fuzzy logic provides an inference mechanism under cognitive uncertainty in reactions to the transport situation danger level, computational neural networks offer exciting advantages, such as learning, adaptation, fault tolerance, parallelism and generalization.[7].

Each neural network input pair is made by two parameters:

- The distance of the vehicle till the trajectories crossing point di;
- Average speed of the vehicle vi.

According to the number of vehicles, neural network has n outputs, and as a result the speed change for the vehicle is output.

Input neurons of output layer has wij, weights and bj shifting.

Each j-th neurons of the ouput layer generates j-th vehicles speed change Δvj.

Values Δv1 ... Δvn are given to the self-training multi-criteria target function F, that evaluate efficiency of the output according the collision possibility P and vehicles common speed change ΣΔvi.

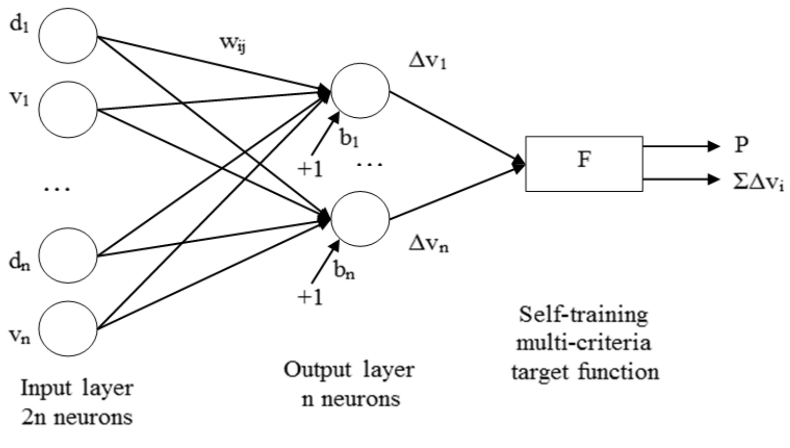


**Figure 1.** Neural network structure.

General fuzzy logic structure, shown in the Figure 1, consists of input as a risk level of recognized objects, membership functions for risk assessment, rule database for selection of actions and defuzzification functions for the level of the activity. In system identification, rule-based fuzzy models are usually applied. In these models, relations among variables are described by means of if–then rules with fuzzy predicates, such as "if the collision possibility is high, then the car speed must be changed" and "if the car speed was changed, but collision possibility still is high, then train speed must be changed".

Fuzzy sets are defined through their membership functions (denoted by μ) which map the elements of the considered universe to the unit interval [0, 1]. The extreme values 1 and 0 denote complete membership and non-membership, respectively, while a degree between 0 and 1 means partial membership in the fuzzy set. A particular domain element can simultaneously belong to several sets (with different degrees of membership).[8] In Figure 2, for instance, 45% of risk belongs to the set of high risk with membership 0.2 and to the set of medium risk with membership 0.8. We can suppose which action must be chosen for the crash prevention after defining the level of the risk in percentages. This gradual transition from membership to non-membership facilitates a smooth outcome of the reasoning (deduction) with fuzzy if–then rules, in fact a kind of interpolation.[8]

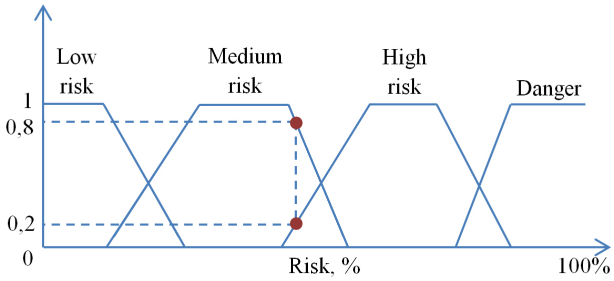


**Figure 2.** Partitioning of the risk domain into four fuzzy sets.

The neuro-fuzzy system of smart transport infrastructure for road traffic safety system consists of movable and stationary controllable components of the system, i.e. transport units and infrastructure – level crossings (Figure 3).

The system contains centralization software components working in the web environment such as a web-server, database, web interface, dynamic system models and control and optimization modules for long term scheduling and global optimization.

There are communication components ensuring data transmission to or between the components, such as satellite positioning system - GPS, radio frequency modules – RF.

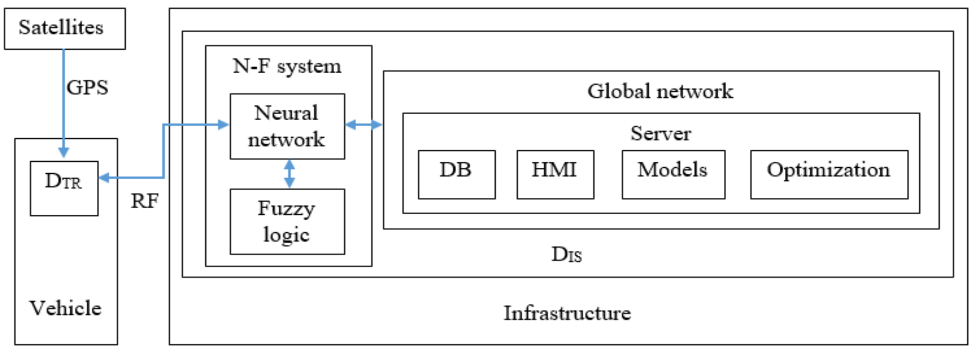


**Figure 3.** Structure of the system.

Each component has embedded electronic device Di, which performs specific function to ensure prevention of collisions between vehicles.

$D_{TR}$ – the devices for transport units obtain the position, calculate the motion parameters and communicate with other devices. The bidirectional energy flow monitoring and measurement [11] and controlling of the energy flow of the drive [12] of the vehicle can be and additional source of data for the system installed in $D_{TR}$.

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$D_{IS}$ – devices of infrastructure objects, such as stations, level-crossings etc. control the anti-collision function. Consist the block of Global network and developed neuro-fuzzy system, for recognizing the collision possibility and possible speed change for the dangerous situation prevention.

## 4. Mathematical model and target function

The mathematical model is represented with following sets:

$U \subset (U_1, \dots, U_n)$ – set of transport units as a subsets of different types, where for different transport safety task it could be:

$U^1 = (U_1^1, \dots, U_{n1}^1)$ – subset of railway transport units

$U^2 = (U_1^2, \dots, U_{n2}^2)$ – subset of road vehicles

$U^3 = (U_1^3, \dots, U_{n3}^3)$ – subset of aerial vehicles etc.

$P = (p_1, p_2, \dots, p_c)$ – set of infrastructure objects, where the collision of vehicles, e.g. for railway transport it could be level-crossings, switches, etc. For this research, the crossing section is assumed as a short straight segment of the route or trajectory.

The geographical coordinates of all crossing of possible routes or trajectories of transport units are defined by these sets:

$$\chi_b^p = \left\{\chi_b^{p_1}, \chi_b^{p_2}, \dots, \chi_b^{p_c}\right\},\ \psi_b^p = \left\{\psi_b^{p_1}, \psi_b^{p_2}, \dots, \psi_b^{p_c}\right\}, \tag{1}$$

$$\chi_e^p = \left\{\chi_e^{p_1}, \chi_e^{p_2}, \dots, \chi_e^{p_c}\right\},\ \psi_e^p = \left\{\psi_e^{p_1}, \psi_e^{p_2}, \dots, \psi_e^{p_c}\right\}, \tag{2}$$

Where

$\chi_b^{p_i}$ – latitude of the beginning point of the crossing sector

$\psi_b^{p_i}$ – longitude of the beginning point of the crossing sector (crossing)

$\chi_e^{p_i}$ – latitude of the ending point of crossing sector

$\psi_e^{p_i}$ – longitude of the ending point of the crossing sector

c – number of trajectories crossing point

$t^p_{vest}$ – safe closing time of each trajectories crossing point $p \in P^2$

Neural network can be used as one of the immune system tool for the situation improvement on the crossing point and transportation process optimization.

There is no information either the output value is correct or not, that is why there is no possibility to use error back propagation algorithm.

Random sequential delta law self-training algorithm and target function was developed for the neural network training.

Function of the optimization is defined by two criteria:

- Collision possibility P with the aim of minimizing;
- Changes of the vehicles' speed $\Sigma\Delta vi$ with the aim of minimizing.

First criterion is connected with safety. The situation considered to be dangerous if trajectories of two transport vehicles has a common crossing point, and exists a possibility, that transport vehicles will arrive at the crossing point of their trajectories at the same time. This situation is actual for each transport type.

Second criterion is connected with the transport traffic specifics. For example train traffic precision is very important for railway transportation operations, because train delays causes obstacles for other trains. That is why timetable is very important for such transport vehicles as trains and trams. Also time of departure and arrival is important for the public transport. That is why it is necessary to make minimal speed changes of such type of vehicles.

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Based on the individual weighted criteria, the target function was developed:

$$F(\Delta v) = \begin{cases} P = \max(P_{IJ}) \rightarrow \min \\ \sum \Delta v_i \rightarrow \min \end{cases} \quad (3)$$

Where,
$\Delta v$ – changes of the speed of vehicle, solution of the task;
P – maximal collision possibility [5,6];
$P_{IJ}$ – each i-th vehicle collision possibility with each j-th vehicle;
$\Delta v_i$ – change of speed of i-th vehicle.

## 5. Algorithm

Developed algorithm consists of such steps:
Initialization:

- Index of training group element e = 1;
- Chosen for the correction neurons sn = 1;
- Chosen for the correction weight sw = 1;
- Retraining = false.

STEP 1. Take the element $e = \{d_1^e, v_1^e, d_2^e, v_2^e\}$ from the training set.
STEP 2. Read the $x_{min}$ and $x_{max}$ parametres, that limit neuron network output.
STEP 3. Calculate output neurons adder values:

$$\Sigma_j = \left(\sum_{i=1}^{2n} x_i * w_{ij}\right) + b_j \qquad j = \overline{1..n} \quad (4)$$

STEP 4. Generate output layer neuron output value by positively and negatively saturated linear activation function:

$$\Delta v_j = \begin{cases} x_{min}, & \Sigma_j \le x_{min} \\ \Sigma_j, & x_{min} < \Sigma_j < x_{max} \\ x_{max}, & \Sigma_j \ge x_{max} \end{cases} \quad (5)$$

STEP 5. Save the previous valuation, if it exists $P^{iep}$, $\Sigma\Delta v_i^{iep}$.
STEP 6. Evaluate the solution, that was found, using the target function $[P, \Sigma\Delta v_i] = F(\Delta v)$.
STEP 7. If $P > P_{lim}$ or $\Sigma\Delta v_i > \Sigma\Delta v_{i\ lim}$, then go to STEP 8.
STEP 8. If the last element of the training set is not reached $e \neq e_{max}$,
then e=e+1 and go to STEP 1,
else if there is no need to retrain the network then FINISH,
else e = 1 and go to STEP 1.
STEP 9. Weight correction occurs sequentially:
If (sn ≠1 and sw ≠ 1) or ($P^{iep} < P$ and $\Sigma\Delta v_i^{iep} < \Sigma\Delta v_i$), that means if the element isn't first and the result is worse than it was before, then return to the previous weight value $w_{sw,\ sn} = w_{sw,\ sn} - k$ and choose another weight
If sw > 2n, then sn = sn + 1, else sw = sw + 1.
If sn > n, then sn = 1, sw = 1.
STEP 10. The correction value is generated, as random number:

$$k = \text{random}(-1000, 1000)/10000 \quad (6)$$

STEP 11. Weight correction is done:

$$w_{sw,\,sn} = w_{sw,\,sn} - k \tag{7}$$

STEP 12. If weight correction was done, than neural network must be retrained. Retrain = true.

STEP 13. Go to STEP 3.

## 6. Neural network training experiment

For the experiment target function was used, but neural network is trained to make a decision about the speed change, to prevent the collision between vehicles.

If common amount of vehicles is n, then neural network has paired input number 2n. Neural network input and output neuron amount is dynamic, because the amount of vehicles can be changed.

Neural network structure is given in the Figure 1.

For the experiment such a situation was chosen: one train; one bus; trajectories of the train and bus have crossing point.

In this situation neural network consists of 4 input and 2 output layers.

Parameters taken for the training set are given in the Table 1.

Each element from the set is sent to the neural network input layer during training process. When changes of speed $\Delta v1$ and $\Delta v2$ for the train and bus are found, these values are evaluated by target function.

Neural network is already trained if:

- Collision possibility is reduced minimum to 0.005;
- Average speed change for the train is not bigger than 3 kmh.

**Table 1.** Neural network training set.

| Number of the training set element | Bus distance till the trajectories crossing point | Train distance till the trajectories crossing point | Bus average speed | Train average speed |
|---|---|---|---|---|
| 1 | 400 | 600 | 40 | 60 |
| 2 | 390 | 580 | 40 | 60 |
| 3 | 320 | 550 | 40 | 65 |
| 4 | 290 | 540 | 40 | 70 |
| 5 | 260 | 520 | 40 | 75 |
| 6 | 230 | 500 | 40 | 80 |
| 7 | 210 | 480 | 40 | 85 |
| 8 | 200 | 460 | 40 | 85 |
| 9 | 190 | 440 | 40 | 90 |
| 10 | 175 | 420 | 40 | 90 |

Two solutions $x_{min}$= -10, $x_{max}$ = 0 un $x_{min}$ = -15, $x_{max}$ = 5 were used for each element of the training sets.

## 7. Neural network self-training experiment

Another experiment was made using the system based on the Waspmote microcontroller. System can evaluate the situation and give an advice to the train or bus driver to change the speed for the prevention dangerous situation.

For the experiment following situation was defined:

- In the road infrastructure is imbedded developed equipment. When car is entering the radio communication channel earshot, it began to send information about its speed, coordinates and trajectory to the infrastructure embedded device.
- When train is entering the radio communication channel earshot, it began to send information about its speed, coordinates and trajectory to the infrastructure embedded device.
- Infrastructure embedded device, which receives data from vehicles makes up neural network based system, which is trained by the target function, find out how to reduce the speed and minimize collision possibility.

For the experiment a single car and train are approaching the trajectory crossing point. The devices of car and train are transmitting the data to the infrastructure embedded device. Initial car distance is 500 m, and train distance is 1000 m, train speed is 80 kmh, but the car speed is 40 kmh. After evaluation of such situation, the collision possibility is 0.469. After data was received, collision possibility P, Train speed change Δv and target function is calculated.

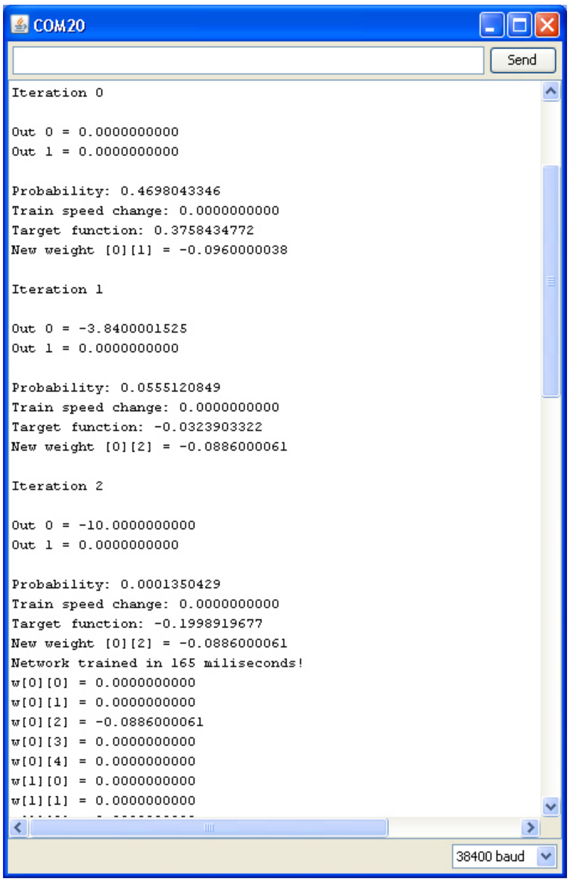


**Figure 4.** Self-training of the system.

In the Figure 4. self-training system is shown. At the beginning collision possibility P was 0.4698043346, and after neural network training process it was reduced to 0.0001350429. Network was trained in 165 miliseconds.

## 8. Conclusions

Analysis of the experiments' results allows concluding following. It's necessary to limit the data output, leaving only the most important data. Limited memory and processing power is the reason for controller to realize the algorithm in a simple form.

The results of research shows that neural network and fuzzy logic can be widely used in traffic safety area, because of its possibility of training and learning and reduced amount of input parameters.

Experiment shows that at the beginning, collision possibility P was 0.4698, and after neural network training process and speed change it was reduced to 0.0001. Experiment took 165 miliseconds, system is working fast and it is very important because of the task specific.

Convolutional neural network wasn't proposed in this study, but authors continue making the research about road traffic safety and plan to develop the CNN based system for the object recognition and collision prevention by using the convolutional neural network and making the decision about how to avoid a dangerous situation on the road.

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