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APPLICATION OF THE ANFIS MODEL IN ROAD TRAFFIC AND TRANSPORTATION: A LITERATURE REVIEW FROM 1993 TO 2018

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Review paper

Abstract: *The paper's focus is on researching the application of the ANFIS (Adaptive Neuro Fuzzy Inference System) model in traffic and transport through a review of relevant papers. The ANFIS, as an element of artificial intelligence, is widely used in intelligent transport systems. All collected papers are divided into 7 sub-areas, namely: 1) vehicle routing, 2) traffic control at intersections with light signaling, 3) vehicle steering and control, 4) safety, 5) modeling of fuel consumption, engine performance and exhaust emissions, 6) traffic congestion prediction, and 7) other applications. For each sub-area, the analysis of the proposed models is performed with a tabular overview of respective input and output variables, while in the third section the discussion of the results is given. It is found that the steering and control of vehicles represent a sub-area with the highest percentage in the total number of examined papers, while the security applications take second place.*

Key Words: *ANFIS, Intelligent Transportation Systems, Light Signaling, Vehicle Routing, Prediction, Modeling*

1 Introduction

The development of science and technology has affected a wider study as well as application of the solutions based on artificial intelligence in various areas. Intelligent transportation systems represent a scientific and engineering discipline that implies integration of modern information and communication technologies into transport infrastructure and vehicles. Therefore, it is evident that smart solutions find their application in this field as well. Some of the most commonly used elements of artificial intelligence are fuzzy logic, artificial neural networks, and genetic algorithms. In addition, there are popular combinations of techniques such as: neuro-fuzzy systems, genetic fuzzy systems, and genetic programming neural networks (Kar et al., 2014).

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Often, though, a realistic system cannot be modeled precisely due to either insufficient or unclear information. When that happens, the solutions based on traditional computer methods do not yield satisfactory results. Therefore, an emphasis is placed on the neuro-fuzzy systems, which represent integration of fuzzy logic and artificial neural networks. Fuzzy logic is an extension of the classical logic so that the variables can have a certain degree of belonging to either true or false. The basic elements for the processing of ambiguities and uncertainty in the fuzzy logic are the fuzzy sets which are mathematically represented by the membership functions. The fuzzy technologies are human-oriented, which means they simulate the human way of thinking and conclusion-making based on the linguistic variables, which are represented by fuzzy sets that linguistic expressions are associated with. In addition to the advantages, some of which are already mentioned, the disadvantage of the fuzzy logic is the impossibility of its adaptation. This problem is solved by artificial neural networks representing models of the human brain with interconnected basic process elements - artificial neurons. The main features that distinguish them are the ability to learn from examples and adaptability, which is characteristic of man, as well as in the case of the fuzzy logic (Arora & Saini, 2014). Each neural network is defined with three properties: the type of artificial neurons, i.e. the type of their transfer function, the connection between the nodes and their structure, and the training algorithm. It can be said that the fuzzy logic and the artificial neural networks complement each other. One of the most commonly used neuro-fuzzy systems is an adaptive neuro-fuzzy inference system (ANFIS), first introduced by Jang 1993 (Jang, 1993). The problems that have led to the development of the ANFIS are the lack of a unique methodology that would transform human knowledge into the base of fuzzy rules, as well as the need for a method that will provide, for certain inputs, the minimum deviation of outputs from the expected values. The ANFIS model is trained by the input-output pairs (vectors), which adjusts the parameters of the membership functions of the input and output variables (Jang, 1996). The training algorithm is hybrid and combines the gradient descend method and the Last Square Estimation (LSE). The fuzzy inference is based on the Takagi-Sugeno system whose typical rule has the form: IF A THEN B, where A and B fuzzy sets are described by the membership functions. The ANFIS has a five-layer structure, and the network is a feed-forward type where neurons transmit their outputs to neuron inputs in the next layer and so on, without a cycle. The most important applications of the observed neuro-fuzzy model are the modeling of non-linear systems, chaotic time series prediction, and clustering.

The main objective of the survey is to review the ANFIS application in the field of road traffic and transportation, as components of the intelligent transportation systems. By searching the Web and the Google Scholar bibliographic database, the papers that deal with this topic since 1993 have been collected. All papers are divided into 7 sub-areas, namely: 1) vehicle routing, 2) traffic control at intersections with light signaling, 3) vehicle steering and control, 4) safety, 5) modeling of fuel consumption, engine performance and exhaust emissions, 6) traffic congestion, and 7) other applications.

Following the introduction, the paper is structured in three sections. The literature review deals with the analysis of papers in individual sub-areas with tabular representations of the variables of the proposed ANFIS models. The discussion is in the third section where the statistical review of the papers by the year of publication is given. On the basis of everything stated in the paper, the last section gives a conclusion.

2 Literature review

2.1 Vehicle routing

An increasing number of vehicles on roads, especially in cities, are causing great traffic jams as existing roads do not have the required capacity. In order to avoid or mitigate this problem, the choice of the optimal route of the vehicle is a very big challenge. Apart from avoiding traffic jams, the optimal route is selected on the basis of several criteria, some of which may be: travel time, distance, fuel consumption, road works, etc. It is evident that it is very difficult to find a route that meets all the requirements. Abbas et al. (2011) propose a model that represents integration of artificial neural networks, a neuro-fuzzy model, and an ant colony optimization algorithm to select the optimal route. All necessary input data are provided by the traffic control center. The proposed model is capable of dynamically adjusting the route change.

The choice of route for transport of dangerous goods in the city is a very complex task. In (Pamucar et al., 2016), a modified ANFIS model with the Dijskstra algorithm for determining the optimal route is proposed, i.e. ANFIS-D model. After training with the artificial bee colony algorithm, for the new input data, the model gives the value of the cost-risk ratio for each branch of the network individually. The role of the Dijkstra algorithm is to find a route in the network that minimizes the total value of the given ratio. The described model was tested in (Pamucar et al., 2016a) in the selection of optimal routes for the transport of oil and oil derivatives in Belgrade, Serbia.

Similarly to the described model, Pamučar & Ćirović (2018) represent the ANFIGS (*Adaptive Neuro Fuzzy Inference Guidance System*) model for choosing the route of vehicle movement under the conditions of uncertainty. In the neuro-fuzzy system the knowledge of the dispatcher is accumulated and seven criteria are defined that influence the selection of the route. The clustering technique is applied in the paper. One of the main advantages of this model is its ability to dynamically adapt to unpredictable events on the route.

In the conditions of natural disasters, it is very important to respond quickly and provide assistance to the affected areas as soon as possible. Under such conditions, the roads are often damaged but other factors that adversely affect the rapid route planning appear as well. Gharib et al. (2018) use the ANFIS in the first step of selecting a route for classification of critical areas into two clusters: 1) areas that can be assisted by road and 2) areas with an access only from the air. Table 1 shows the input and output variables for the listed ANFIS models.

Table 1 Input and output variables of the ANFIS models for vehicle routing

Author/year	Input variables	Output variables
Abbas et al. (2011)	Distance; traffic flow; environment monitoring; width; road condition; traffic lights	Pheromone level (ant colony)
Pamučar et al. (2016), Pamučar et al. (2016a)	Carrier's operating costs; emergency response; risk associated with the environment; risk of an accident; consequences of an accident; risk associated with infrastructure; risks of terror attack/hijack	Cost/risk value
Pamučar & Ćirović (2018)	Type of road surface; travel distance; travel time; route capacity; traffic capacity; road capacity; the existence of alternative roads along the length of the route	Preference of the dispatcher to select a particular route
Gharib et al. (2018)	Road slope; weather conditions; intensity of disaster; population density; road risk; distance of vehicle; distance from airport; road width	Cluster (1 or 2)

2.2 Traffic control at intersections with light signaling

The application of light signalization to control traffic at intersections is one of the most common and most effective methods. However, a great lack of this kind of regulation is that the intervals are fixed, which can often cause unnecessary delays and congestions. An intelligent solution consists in forming an adaptive model that adjusts intervals to the real state of traffic at the intersection. Such a model is presented in (Udofia et al., 2014). Its basis is the ANFIS model with two inputs. For training data, the urgency degree as an output variable is calculated analytically based on the input variables for each phase of the crossroads individually. The model uses real data collected by the sensor and gives a certain output based on them. The next green interval is assigned to the phase with the highest urgency degree. The model was tested at a real intersection and the results confirm its effectiveness. The described ANFIS model is also used in (George et al., 2015) within a system that receives incoming traffic data from the processing of video data. Lai et al. (2015) also use the same inputs, while the output variable is an extension time of the duration of the green light interval. The testing has found that the performance of the proposed model is better than that of the traditional and fuzzy controllers. The ANFIS traffic control model can also be tested using the graphical user interface in the MATLAB software package, which was done in (Abiodun et al., 2014). The model proposed in (Wannige & Sonnadara, 2008) has two inputs representing the number of vehicles entering the intersection in both directions. The model training was performed for the given input values and for calculating an optimal time of the green light interval based on them. According to Seesara & Gadit (2015), two input variables were selected based on the advice of competent institutions and traffic experts. In this paper, comparison of performance is performed between the ANFIS and the fuzzy controller with the ANFIS giving better results. Arraghi et al. (2014) observe four input variables for traffic control at the four-way intersection. In this case, the ANFIS justifies the application because it shows better testing results than fuzzy controllers and fixed-time models. Korkmaz & Akgüngör (2016) use the ANFIS to model vehicle delays at vehicle intersection, and, according to Gokdag et al. (2007), a model of the same purpose has a different set of input variables. Comparison of the prediction results with those of the usual methods, such as Webster, HCM, DDF and SSM, indicates that the ANFIS represents a very promising modeling method. Testing was carried out in the case of an intersection in Erzurum, Turkey. Similar research is also presented in (Hasiloglu et al., 2014), where comparison was done, instead of the DDF, with the Multiple Regression Analyzes method. The observed variables are the same for the two above mentioned models. Table 2 provides an overview of the input and output variables of the ANFIS models by authors.

Table 2 Input and output variables of the ANFIS model for traffic control at intersections with light signaling

Author/year	Input variables	Output variables
Udofia et al. (2014)	Waiting time; queue length	Urgency degree
George et al. (2015)	Waiting time; queue length	Urgency degree
Lai et al. (2015)	Waiting time; queue length	Extension time of the next phase
Abiodun et al. (2014)	Number of vehicles on the arrival side; number of vehicles on the queuing side	Extension time of green light
Wannige & Sonnadara (2008)	Vehicle inflow in two roads	Green light time of one lane
Seesara & Gadit (2015)	Arrival rate of the particular phase; last time vehicles that have not passed during last green phase	Green time extension
Arraghi et al. (2014)	Queue length of vehicles at each approaching link (for 4 links)	Green time for the current phase
Gokdag et al. (2007)	Time; number of approaching vehicles in the green duration; number of queuing vehicles in the red duration	Vehicle delay
Korkmaz & Akgüngör (2016)	Cycle time of signalization; green time; degree of saturation	Vehicle delay
Hasiloglu et al. (2014)	Time; number of approaching vehicles in the green duration; number of queuing vehicles in the red duration	Vehicle delay

2.3 Vehicle steering and control

A large number of controllers for control and stability in vehicles are based on neuro-fuzzy systems. Selma & Chouraqui (2012) propose ANFIS models to control vehicle paths based on previous training. Two models for positioning the X and Y axis have been developed. The model was tested by the simulation method and the results show its efficiency. According to Saifizul et al. (2006), the ANFIS model for steering has the task of keeping the lateral error and the yaw error at an acceptable level while driving. In this case, the input data are collected by means of camera on-board, which is a much simpler solution than the existing ones, which implies the installation of a magnet or wiring on the road. The ESC (Electronic Stability Control) is an unavoidable system in newer cars that significantly improves passenger safety. The ECS systems mainly use measured yaw velocity of the chassis and the sideslip angle (the angle between the directions of the vehicle's velocity and its chassis). The problem is the determination of the given angle because it is difficult to measure with the sensor. A Sideslip angle modeling involves the use of various methods, and Boada et al. (2015), propose ANFIS for this purpose. In (Boada et al., 2016), the same author uses the Kalman filter to evaluate the Sideslip angle, in combination with the ANFIS model. However, Hou et al. (2008) uses the Sideslip angle as one of the input variables in the integrated chassis control model. Model training and testing are carried out using the simulation method.

Automatic transmission control in modern vehicles is done with the computer that selects the optimal shift based on the input signals received by the sensors. However, in some driving conditions such a system is not efficient (low speed, vehicle load, etc.). A potential solution is presented in (Li et al., 2007) and is based on the ANFIS model. Perez et al. (2010) present an ANFIS model for controlling the braking and acceleration of autonomous vehicles that tend to expand in the future. The tests confirm the efficiency of the ANFIS model in determining the value of the output variables. Autonomous vehicles and the ANFIS model are also studied in (Al Mayyahi et al., 2014), where four such models are developed to avoid obstacles and reach the desired position.

When it comes to electric vehicles, using the observed neuro-fuzzy model in the regenerative braking system, it is possible to provide greater autonomy (Sindhuja et al., 2014). The system involves the use of an electric motor as a generator in braking, thus recycling the spent energy into a rechargeable battery. The ANFIS model is also applicable in the case of hybrid drives where it minimizes engine fuel consumption with internal combustion and maximizes torque (Mohebbi et al., 2005). Eski & Yıldırım (2017) describe the use of ANFIS model for the electronic regulation of throttle of heavy vehicles. Car parking is a demanding action, sometimes for experienced drivers, and if it is a truck with a trailer, the problem becomes very complex. Due to the non-linearity of the movement of such a vehicle, the observed neuro-fuzzy system was applied by Azadi et al. (2013). In the first stage of the proposed model, the vehicle in advance takes an adequate position in order to then position it back to the parking place. The use of sensors that provide environmental information is unavoidable in this case.

Several authors dealt with the use of an ANFIS suspension model to improve safety and travel comfort (Shuliakov et al., 2015; Nugroho et al., 2014;

Kothandaraman & Ponnusamy, 2012). Depending on the input data, the model is capable of adapting the characteristics of the shock absorbers and other elements that make up the mentioned system. An overview of the input and output variables of some ANFIS models with application in vehicle steering and control systems is shown in Table 3.

Table 3 Input and output variables of the ANFIS model in vehicle steering and vehicle control systems

Author/year	Input variables	Output variables
Selma & Chouraqui (2012)	X position, Y position	X position, Y position
Saifizul et al. (2006)	Lateral error; angle between longitudinal direction and local road tangent at look-ahead distance; yaw rate	Steering angle
Boada et al. (2015); Boada et al. (2016)	Lateral acceleration; yaw rate; steering angle; longitudinal velocity; yaw rate/longitudinal velocity	Sideslip angle
Hou et al. (2008)	Yaw velocity discrepancy; sideslip angle discrepancy	Brake/Throttle
Li et al. (2007)	Vehicle velocity; air damper angle	Shift point
Perez et al. (2010)	Speed error; acceleration	Brake/Throttle
Sindhuja et al. (2014)	Distribution of braking force; (front)battery's state of charge (SOC); speed of the motor	Braking force ratio
Al Mayyahi et al. (2014)	Angle difference (for the first and second controller); front, right and left distance (for for the third and fourth controller)	Right/left angular velocity
Mohebbi et al. (2005)	Desired torque; battery's state of charge (SOC)	Throttle angle of the internal combustion engine
Eski & Yıldırım, (2017)	Two different random inputs of the heavy duty vehicle speed	Servo motor speed
Azadi et al. (2013)	Tractor yaw angle; trailer yaw angle; horizontal distance from the wall	Steering angle
Shuliakov et al. (2015)	Turn rate; angular transducer output	Deviation angle of a stabilization object
Nugroho et al. (2014)	Velocity of sprung mass (car body); relative velocity between sprung mass and unsprung mass/velocity of unsprung mass (wheel); relative velocity between the sprung mass and unsprung mass	Fuzzy-skyhook force/fuzzy-ground force
Kothandaraman & Ponnusamy, (2012)	Suspension deflection; sprung mass velocity	Actuator force

2.4 Safety

Security has always been the highest priority in traffic, and today a large number of technologies (video surveillance, speed control, etc.) are present within intelligent transport systems, which have the task of raising safety to an even higher level (Rahimi, 2017). Every day, an increasing number of vehicles are in the streets and so are drivers who do not share the same experience and abilities. Statistics say that the driver's behavior is the main cause of traffic accidents. Bearing this in mind, a number of authors have paid attention to the development of various driver behavior prediction models, some of which are listed in (Kumar & Prasad, 2015).

The ANFIS application for the car following model is presented in (Poor et al., 2016; Khodayari et al., 2010). Similarly, Ghaffari et al. (2015) represent a new approach to modeling the car following when changing the lane of the leading vehicle. Such a maneuver can be viewed as a transient condition because the vehicle deviates from the conventional modeling for a certain time. The same author deals with the modeling of the overtaking path in (Ghaffari et al., 2011, 2011a), as one of the most demanding traffic operations.

Modern Collision Avoidance Systems involve the use of various sensors in order to collect the data necessary for determining the parameters. All this raises the price and complexity of such systems. Bearing this in mind, Saadeddin et al. (2013) develop a low-cost system based on a combination of the INS (*Inertial Navigation System*) data and a GPS (*Global Positioning System*) in their research. This integration is realized through the IDANFIS (Input-Delayed ANFIS). The data provided by satellite systems have been used as inputs in (Sun et al., 2017) in combination with a neuro-fuzzy model to develop a rear-end impact prevention system.

Dadula & Dadios (2016) represent an ANFIS which has the function of detecting critical events in public passenger transport based on characteristic sounds. The system can differentiate the normal circumstances from alarming (e.g. shooting) with a high percentage of accuracy.

Pedestrians are a very vulnerable group of participants in the traffic. For the sake of their protection, various mechanisms can be implemented in intelligent transport systems. One of them is modeling the pedestrian decision to cross the street with the help of artificial neural networks and the fuzzy logic, as presented in (Ottomanelli et al., 2010).

Determining critical points along the road can be of great use in preventing traffic accidents. In the case that statistical methods cannot provide reliable results, e.g. because of the lack of data, the authors use the observed neuro-fuzzy system that, based on the physical characteristics of the path and environmental factors, predicts the risk spots. Such studies are presented in (Hosseinlou & Sohrabi, 2009; Effati et al., 2014). Prediction of traffic accidents in real time using ANFIS is presented in (Liu & Chen, 2017). The authors analyze the traffic flow factors just before an accident occurs. By comparing the results with other models, it can be concluded that the ANFIS in this case also shows better performance.mTraffic sign detection is an important part of the Driver Assistance System because it allows automatic adjustment to the conditions prescribed for them. Billah et al. (2015) propose an ANFIS model for the recognition of circular signs based on the data obtained by image processing and video processing. The recognition accuracy is more than 98%, which sufficiently highlights the model's capabilities.

In order to improve the vehicle stability as well as its handling, it is important to adjust the speed to the road geometry. The model that performs this function is presented in (Wankhede et al., 2011). Its output represents a certain degree of acceleration or deceleration of the vehicle, depending on the current acceleration and winding of the road. Table 4 provides an overview of the security applications of the ANFIS model with input and output variables.

Table 4 Input and output variables of the ANFIS model in security applications

Author/year	Input variables	Output variables
Poor et al. (2016)	Distance difference (between cars); velocity difference; speed of the front car; driver reaction time	Acceleration of following vehicle
Khodayari et al. (2010)	Relative speed; relative distance; acceleration of leading vehicle	Acceleration of following vehicle
Ghaffari et al. (2015)	Distance between follower and front vehicle; relative acceleration of these two vehicles; velocity of follower; acceleration of follower	Acceleration of following vehicle
Ghaffari et al. (2011)	Lateral coordinate; longitudinal coordinate; velocity; acceleration; movement angle;	Lateral coordinate; longitudinal coordinate
Ghaffari et al. (2011a)	Velocity; acceleration; jerk; heading angle; heading angle race	Acceleration; heading angle
Saadeddin et al. (2013)	Position and velocity components (x, y, and z axis) from INS	Error in INS position and velocity
Sun et al. (2017)	Relative Distance; relative velocity; relative heading	Warning status
Dadula & Dadios (2016)	12 mel Frequency Cepstral Coefficients (MFCCs) for each audio frame	Crisis condition or normal condition
Ottomanelli et al. (2010)	Vehicle's speed; vehicle's distance; interval between vehicle arrival and pedestrian arrival at the crossing (or gap)	Decision (wait or cross)
Hosseinlou &	Topographical and geometrical	Accident frequency of the

Sohrabi (2009)	drawings of the road; amount of traffic volume per day; amount of hourly traffic volume in the day	road
Effati et al. (2014)	Roadway geometry; environmental factors	Danger value
Liu & Chen (2017)	Average speed; volume; occupancy in 30-second aggregation intervals (9 traffic flow variables)	Crash risk value
Billah et al. (2015)	Total black pixel; entropy; contrast; correlation; energy; homogeneity	Label which means a specific sign
Wankhede et al. (2011)	Angle curvature; acceleration	Acceleration

2.5 Modeling of fuel consumption, engine performance and exhaust emissions

Fuel consumption in the world is growing rapidly every day, while, at the same time, the world reserves are decreasing. In addition to the problem of energy shortages, the problem of increasing pollution is present, that is, the problem of harmful substances emissions into the atmosphere. Traffic and transport activities constitute a very large share of the total fuel consumption, and therefore, studies have focused on optimization. To do this, it is necessary to develop models for the consumption prediction. The model presented in (Massoud et al., 2014) takes into account the interaction of transport and land use in urban areas so that the planners can efficiently analyze and plan fuel consumption. When it comes to passenger cars, the ANFIS prediction model is proposed in (Syahputra, 2016; Atmaca et al., 2001). According to Abdallat et al. (2011), using the given model, it is possible to estimate the need for the amount of fuel for the transportation of the whole country. In the concrete case, the research was carried out for Jordan.

Diesel fuel is mostly used for trucks, and in order to reduce CO_2 emissions, the use of alternative fuels, such as biodiesel, is increasingly considered. Many studies deal with analyzing the effects of the addition of diesel fuel. The authors propose ANFIS models that have the task of predicting engine performance and concentration of harmful substances of exhaust gases when using such mixtures (Hosoz et al., 2013; Özkan et al., 2015; Ghanbari et al., 2015; Rai et al., 2015). Table 5 provides an overview of the ANFIS model with application in modeling fuel consumption, engine performance and exhaust emissions.

Table 5 Input and output ANFIS variables for modeling fuel consumption, engine performance and exhaust emissions

Author/year	Input variables	Output variables
Massoud et al. (2014)	Land use; transportation	Energy consumption
Syahputra (2016)	Car weight; year	Miles per gallon
Atmaca et al. (2001)	Car weight; year	Miles per gallon
Hosoz et al. (2013)	Biodiesel content in the fuel; engine speed; engine load	Brake power; brake specific fuel consumption; brake thermal efficiency; emissions of HC, CO, NO; exhaust gas temperature
Özkan et al. (2015)	Types of engine fuels; injection pressure; speed	Torque; specific fuel consumption; air consumption; efficiency; lambda values
Ghanbari et al. (2015)	Diesel–biodiesel and nano particles blends; speed	Engine power; torque; brake specific fuel consumption; emission components
Rai et al. (2015)	Percentage load; percentage liquefied petroleum gas; injection timing	Brake specific energy consumption; brake thermal efficiency; exhaust gas temperature; smoke
Abdallat et al. (2011)	Annual number of vehicles; vehicle owner level; income level; fuel prices	Energy consumption (in tons of oil)

2.6 Traffic congestion prediction

Traffic congestion is a part of everyday life in big cities, which has a negative impact on life quality because of considerable time spent. In addition to time expenditure, it is necessary to consider higher fuel consumption, which means more air pollution. Due to a number of problems caused by traffic jams, intelligent transportation systems should provide mechanisms to anticipate and avoid them (Joshi & Hadi, 2015). Zaki et al. (2016) present a framework for short-term prediction, where, apart from the ANFIS, a model based on the Hidden Markov Models is being developed. The same variables are taken into account by Shancar et al. (2012) in their model. Kukadapwar & Parbat (2015) represent an ANFIS model that uses real-time traffic data for the prediction of jams in Nagpur city, India. An overview of these models is given in Table 6.

Table 6 Input and output variables of the ANFIS model for predicting traffic congestion

Author/year	Input variables	Output variables
Zaki et al. (2016)	Speed; density	Level of congestion
Kukadapwar & Parbat (2015)	Speed reduction rate; proportion of time traveling at very low speed (below 5 kmph) compared with total travel time; traffic volume to roadway capacity ratio	Congestion index
Shankar et al. (2012)	Speed; density	Level of congestion

2.7 Other applications

For the purpose of surveillance, future planning and efficient management of the transportation system of a country, it is necessary to have accurate data on the classes and number of vehicles. Intelligent transportation systems include various technologies, and the observed neuro-fuzzy vehicle classification system is proposed in (Maurya & Patel, 2015). The authors take into account the physical dimensions of the vehicle, such as the wheelbase and the average distance of the wheels on the same track.

Vehicle activated signs to warn drivers of over speeds are a very useful mechanism for intelligent transportation systems. However, if the threshold of speed is adapted to the conditions and dynamics of traffic, the benefits become even greater (Jomaa et al., 2015).

The prediction of travel time can be realized mostly on the basis of statistics or artificial neural networks. Statistical solutions often do not yield satisfactory results due to the non-linear nature of the dependencies of the observed variables. Therefore, the application of neural networks, more precisely the ANFIS model is more appropriate in this case (Maghsoudi & Moshiri, 2017).

Thipparat & Thaseepetch (2012) propose an ANFIS model for predicting the possibility of sustainability of the highway construction. At the design and planning stage, expert knowledge is collected in order to evaluate some of the influential factors and, based on this, deduce the conclusion on sustainability.

The selection of an optimal vehicle for transportation in the Serbian army based on a given neuro-fuzzy model was presented in (Pamučar et al., 2013). The model is capable of simulating the decision-making process, as do logistics officers.

In (Ghaffari et al., 2012), the subject of research is a prediction of the future status of the vehicle with the Stop&Go system. The developed model can reduce the likelihood of impact on the rear of the vehicle, and in addition, improve the comfort experience during city driving.

Since traffic is an important source of noise, Sharma et al. (2014) present an ANFIS model for predicting the value of the mentioned variable. Vehicle speeds, traffic flows and the use of siren can be listed as the main influencing factors. Table 7 provides an overview of the ANFIS model with applications in intelligent transportation systems.

Table 7. Input and output variables of the ANFIS model for various applications in intelligent transportation systems

Author/year	Input variables	Output variables
Maurya & Patel (2015)	Wheelbase; average track	Light commercial vehicle/ car-jeep-van/two axle trucks-bus/three axle truck/ multi axle trucks
Jomaa et al. (2015)	Time of day; traffic flow; standard deviation of mean vehicle speeds	85^{th} percentile speed for each hour on the day
Maghsoudi & Moshiri (2017)	Vehicle speed; road occupation coefficient; traffic flow	Travel time
Thipparat & Thaseepetch (2012)	Geometrics and alignments; earthworks; pavement; drainage; retaining walls; slope protection; landscape and ecology… (14 groups, 60 variables)	Sustainability level of highway design
Pamučar et al. (2013)	Reliability of the means of transport; mobility of the means of transport in field conditions; exploitation of the cubage of transport; cost of tonal kilometer	Preferential dispatcher
Ghaffari et al. (2012)	Relative speed; relative distance; acceleration of follower vehicle; velocity of follower vehicle	Acceleration of follower vehicle in next steps
Sharma et al. (2014)	Road traffic flow; vehicle speed; honking	Traffic noise

3 Discussion

The adaptive neuro-fuzzy inference system provides wide application in road traffic and transportation. In this review, 62 papers were collected for a period of 25 years of its study. Fig. 1 shows the number of papers published per year. It can be concluded that the application of the ANFIS in the observed area was not the subject of research until 2001, followed by a break until 2005. Since then, the number of papers per year has grown exponentially in order to record the highest value in 2015. Nevertheless, in the last few years, there has been a clear decrease in interest in studying the given topic.

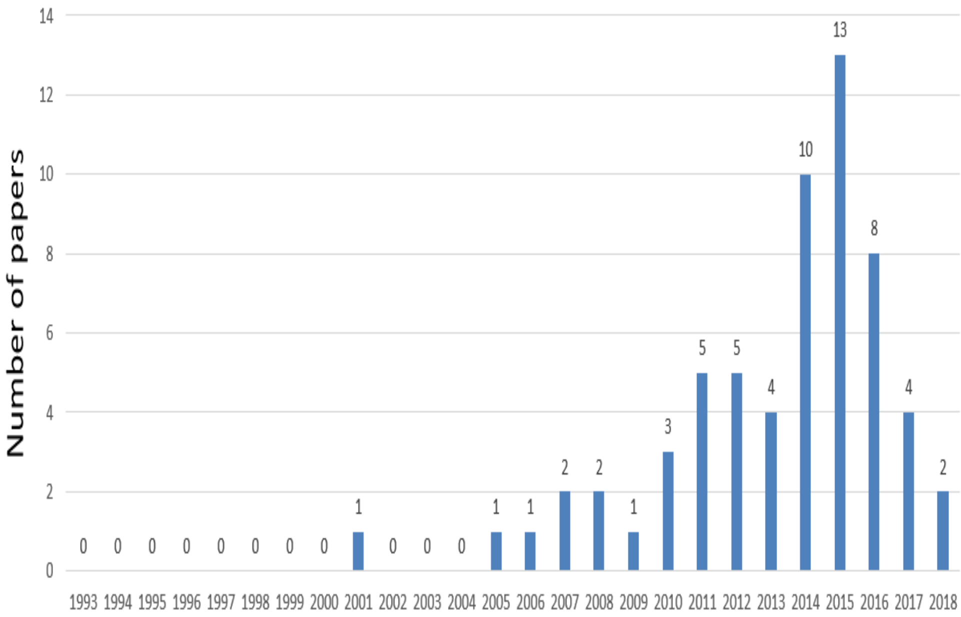

Fig. 1 Number of papers per years

The collected papers are divided into 7 sub-areas, as already discussed in Section 2. Fig. 2 shows percentage share of the papers from each sub-area in the total number. It is obvious that the vehicle steering and control make up the largest percentage, 24%, and the safety is immediately behind with 23%.

Ultimately, the ANFIS application in the area of vehicle steering and control, in addition to driving comfort, aims at increasing passenger safety. The smallest number of authors dealt with predicting traffic congestion with the help of the observed neuro-fuzzy model.

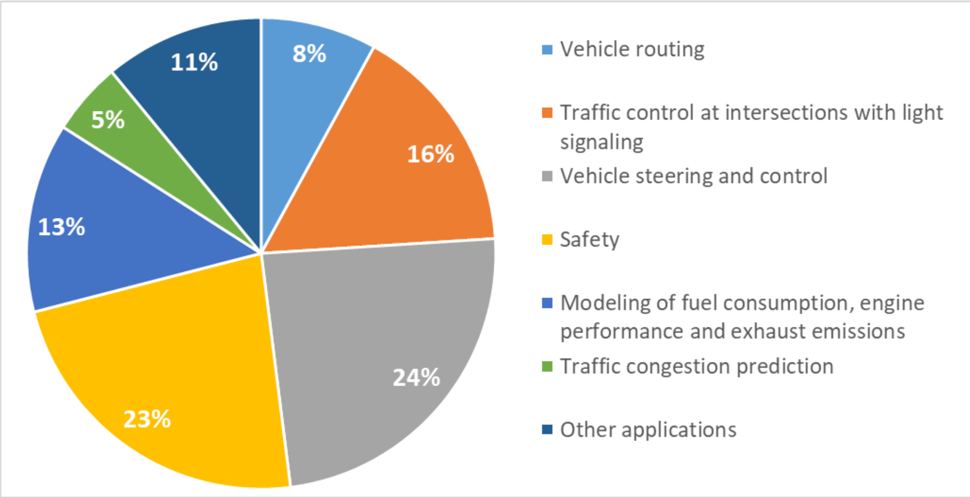

Fig. 2 Participation of individual sub-areas in the total number of collected papers

Table 8 gives an overview of the number of papers by individual areas and by year of publication, with the years with no posts left in Table. If observed in 2015, the greatest number of papers is published from the sub-area of traffic control at intersections with light signaling and modeling of fuel consumption, engine performance and exhaust emissions. The second year in terms of the number of published papers is 2014 where the largest number of papers is from the sub-area of traffic control at intersections with light signaling.

Table 8 *Number of papers by sub-areas and year of publication*

Year	VR	TC	SC	S	MF	CP	OA
2001					1		
2005			1				
2006			1				
2007		1	1				
2008		1	1				
2009				1			
2010			1	2			
2011	1			3	1		
2012			2			1	2
2013			1	1	1		1
2014		4	3	1	1		1
2015		3	2	2	3	1	2
2016	2	1	1	2	1	1	
2017			1	2			1
2018	2						

* VR – vehicle routing; TC – traffic control at intersections with light signaling; SC – vehicle steering and control; S – safety; MF – modeling of fuel consumption, engine performance and exhaust emissions; CP – traffic congestion prediction; OA – other applications

The total number of the sources dealing with the topic 60, comprising 41 journals and 19 conferences. When it comes to the number of papers published by a single source, only two magazines have two published papers, namely,

- Mechanical Systems and Signal Processing, and
- International Journal of Scientific and Engineering Research.

Depending on the purpose of the ANFIS model itself, authors use different input and output variables, but in a single sub-area, there are many cases in which they have opted for the same. The sets of values of the observed variables are obtained mainly in two ways, which are measurements and simulation methods in one of the softwares. Also, model testing and validation are in many cases performed in a simulation environment. For the functioning of ANFIS in real systems, such as road vehicles and generally intelligent transportation systems, sensors play a key role in providing input data. Model outputs are forwarded as information to the user or used as an input of an actuator or a separate system that needs to perform a particular action.

The basic limitation of this paper is the possibility of not including or failing to find all the referential papers from the observed area. In addition, papers in non-English languages are not taken into consideration.

Conclusions

The paper analyzes the application of the ANFIS model in the field of road traffic and transportation. It presents an overview of the papers, while the proposed models for specific purposes are theoretically analyzed with the results tabulated and graphically presented. It can be concluded that the use of ANFIS in traffic is largely due to its ability to model non-linear systems ans well as its ability of adaptability (learning from examples). A key step in developing the ANFIS model is the correct choice of input variables depending on the desired output. In addition, in order for the model to be trained, it is necessary to collect adequate data. The results of the testing of the observed model show its superiority in comparison to the classical, previously used models. Some authors combine the ANFIS with other techniques; hence, such modified models as ANFIS-D and ANFIGS. Given that the field of intelligent transport systems develops every day, new opportunities for potential applications of ANFIS are being created. Sensors for data acquisition have a very important role as the goal is to provide accurate inputs to the model. Future research could aim at analyzing the ANFIS model application to other modes of transport.

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