# Artificial Intelligence in Industry 4.0: The future that comes true: AI

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# Use of Artificial Intelligence in Traffic Technology and Transport

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***Abstract:*** *This article presents the application of various artificial intelligence technologies in the field of intelligent transport systems. Examples of research into the application of expert systems based on ANFIS technology in motorway traffic safety control and urban mobility assessment are described. In addition, the results of scientific research on the application of learning agents in traffic control are presented.*

***Keywords:*** *Intelligent Transport Systems, Artificial Intelligence, Expert Systems, ANFIS, Intelligent mobility, Traffic control, Learning agents*

## 1. Introduction

The use of artificial intelligence (AI) in the field of IntelligentTransport Systems (ITS) has become increasingly important. Today's traffic and transport systems generate vast amounts of data in real time, where AI algorithms offer innovative solutions to improve traffic flow, reduce congestion, and increase overall transport efficiency, [1, 2, 3]. In addition, one of the key advantages of artificial intelligence is its ability to analyze real-time traffic data from various sources, such as cameras, sensors, GPS devices, etc. By leveraging this data, AI algorithms can identify behavioral patterns and process trends. These real-time analyzes enable traffic management systems to make decisions and implement dynamic management strategies to improve traffic flow, especially in the most congested areas, [4]. This includes adaptive traffic control systems as another application of artificial intelligence. These systems use AI algorithms to adjust the timing of control signals based on current traffic conditions. This proactive approach to traffic control has proven to be very effective in reducing congestion and improving the overall driving experience. In addition to real-time data analysis and adaptive signal control, predictive analytics algorithms are also used to predict traffic patterns and identify potential critical areas of congestion, [5, 6]. By analyzing historical data and trends, these algorithms can predict future traffic conditions, allowing proactive measures to be taken to alleviate congestion before it occurs. By using effective AI algorithms to analyze data in

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real time, optimize traffic flow and predict traffic patterns, it enables more sustainable traffic systems.

The Expert System is branch of artificial intelligence (AI) which is utilized to address complex problems by utilizing human knowledge on various areas for analysis and decision making. By definition, an expert system is a computer program that manipulates facts, knowledge, and reasoning to solve problems efficiently and effectively in a narrow problem area that normally requires various expensive sources of knowledge and human experts. Expert systems operate similar to human experts, which use symbolic logic and heuristic rules to propose result, and they are characterized by some advantages compared to humans.

This paper presents two applications of expert systems based on ANFIS architecture: Decision support system for motorway safety management and Expert system for urban mobility estimation,[7, 8].ANFIS architecture is based on fine-tuning of fuzzy causal IF-THEN rules and enables work with large data sets. The advantage of ANFIS is that it combines fuzzy decision-making ability with the learning ability provided by the neural network to model the dynamics of different nonlinear systems (universal approximation), [9, 10].ANFIS usually is created as a five-layer network of multilayer perceptron (MLP), Fig. 1.

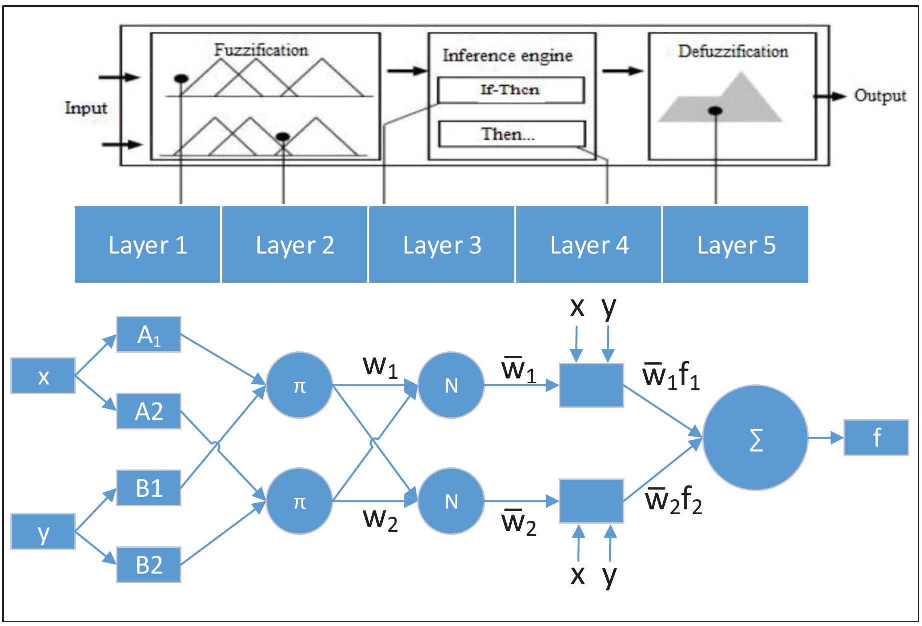


*Figure 1. ANFIS network architecture [7]*

One area where AI is applied very successfully is traffic control. It is an important service in the scope of Intelligent Transportation Systems (ITS). Today, traffic control must solve the problem related to everyday congestion, and significant short or long term changes in traffic demand. Especially in urban environments where urban motorways [11] and signalized intersections [12] are the two most important use cases for ITS traffic control services. An often applied learning approach to obtain a control law capable of solving significant changes in traffic demand is Reinforcement Learning (RL). The concept of learning agents and their application in traffic control on urban motorways and for signalized intersections is elaborated in forth chapter.
Generally, an agent in AI is a structure that can learn from previous experience and improve its performance during operation. Usually, it is applied as software connected with sensors to measure the state of its working environment containing internal logic to create output via actuators to change the state of the working environment according to a defined performance criteria function. There exists a class of cooperative agents that have communication capabilities to exchange information with other (neighboring) agents to improve global performance when dealing with larger complex systems like urban transportation networks.

## 2. Use of Expert Systems to Motorway Safety Management

In this approach, the fundamental part of the real-time motorway safety management system is ANFIS, serving as a pivotal machine learning technology. Leveraging predefined algorithms and assimilated rules derived from the Crash potential model [7], the system generates recommendations for optimizing motorway signalizations. Essentially, there are two primary systems influencing traffic: variable message signs (VMS) and the implementation of suitable variable speed limits (VSL) signs. With its capacity for learning, the system adapts and applies the most effective solutions based on past experiences.
The architectural proposal for the decision support system in motorway safety management is depicted in Fig. 2 [7]. Thorough testing on simulation models and selected trials is imperative for the future implementation of these technologies. In this context, analyzing driver behavior regarding adherence to speed limits is particularly crucial, serving as a fundamental prerequisite for the successful adoption of this motorway safety management approach.
During the training phase, ANFIS learns from a dataset by adjusting the parameters of the fuzzy IF-THEN rules and the neural network. This is typically done using a technique like backpropagation or gradient descent to minimize the error between the actual and predicted outputs.Once trained, ANFIS can make predictions or decisions based on new input data. It uses the fuzzy IF-THEN

rules to fuzzify the input variables and propagate this information through the neural network to produce crisp output values.One of the key strengths of ANFIS is its ability to adapt and refine its rules and parameters based on new data or changes in the environment. This adaptability allows it to continuously improve its performance over time.

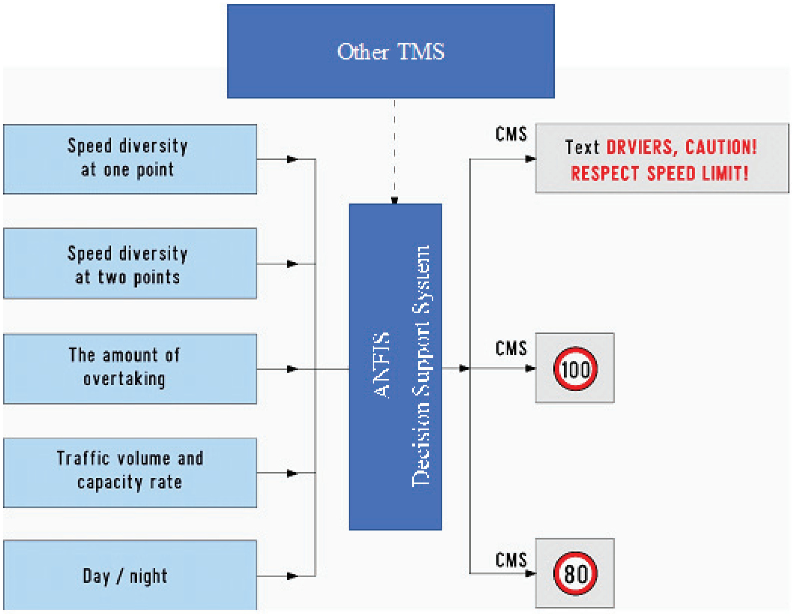


*Figure 2. Decision support system architecture [7]*

The true benefits of the approach outlined in this paper can be fully realized through cooperative traffic management systems [5]. By employing the cooperative intelligent vehicle speed adaptation system, issues related to driver compliance with speed limits are effectively addressed and mitigated.

## 3. Expert System for Urban Mobility Assessment Based on the Application of Artificial Intelligence Technologies

Urban mobility is defined as the movement of people between sources and destinations, at various times, by different means of transport and modes of travel for achieving different goals.[13] The issue with urban mobility estimation is that currently proposed methods are characterized by number of shortcoming, since each research area (city) has its own characteristic that has to be taken into account. Therefore, since the mobility assessment should be based on objectively measured parameters, it requires expert knowledge that can quantify the assessment value regarding the state of urban mobility based on measured parameters. Without embedded expert knowledge, the system itself is incapable of provision of conclusion if the state of the mobility in observed area is satisfactory and by which grade it can be assessed. The goal of the expert system is to be applicable on as large number of cities as possible.

To build ANFIS based expert system for urban mobility assessment expert knowledge is required, that will be applied over objectively measured mobility indicators. Those mobility indicators have to be selected in the way that they are universally accessible and available, in order to mitigate the impact of diversity and variety of mobility data that may come from different sources. Therefore, the public mobile telecommunication network has been identified as primary data sources, since it’s potential as data source for urban mobility related application has been proved by number of researchers[14]. Both telecom network Call data records (database storing records for billing purposes) and signaling data (communication data among different network elements, obtained by probes) have been used for anonymized population migration analysis, resulting in following indicators: origin destination matrixes data (representing the volume of migrations in a unit of time); distance matrix (average distance per user migration among two spatial units, represented by either Euclidian distance, or road distance od most likely itinerary obtained from external source); and travel time matrix (average travel time per user migration among two spatial units), [15]. In order to generate expert opinion, those parameters have to be fuzzified based on following principle. Indicator trip duration is divided into three categories: Short trip duration (up to 33% of the longest lasting trip), Medium trip duration (from 34% to 66% of the longest lasting trip) and Long trip duration (from 67% to 100% of the longest lasting trip). The same principle is applied to other indicators.

ANFIS process overview is presented in Fig. 3.

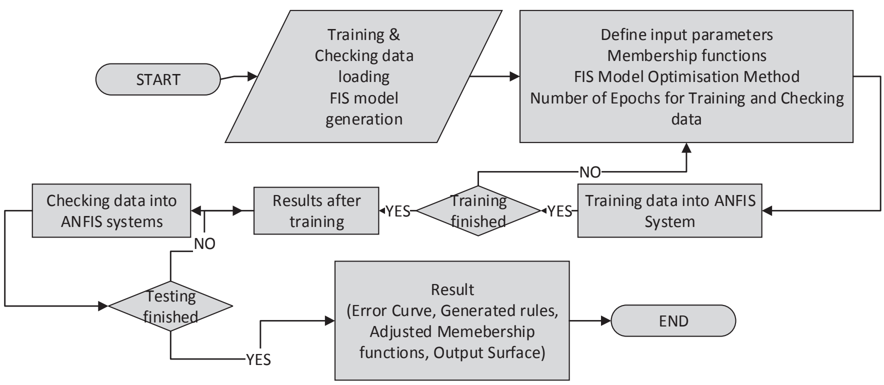


*Figure 3. ANFIS model creation process, based on [9], [10]*

The experts (urban mobility professionals, i.e., academics, experts from the private sector, city planners…) are then utilized and presented with a number of scenarios that they have to evaluate in terms of mobility assessment. Their feedback reflects the relationships between the fuzzified values of the mobility indicators and the mobility assessment which are the used for model training. The model is described with rules, each including respective interval of the mobility estimate output values, depending on the values of the input variables. Before the model learning initial rule base is set and the values of the target variable (mobility assessment values) are unknown. Following the model learning process (selection of model with lowest prediction error), ANFIS enables the creation and fine-tuning of rules which describe the behavior of a complex system and enables presentation of mobility assessment as a single number, considering the values of all indicators. Since it is based on generally accessible data source and universally applicable methodology, this AI based model is capable on calculation of urban mobility estimate grade that is comparable to itself (during different time periods) and to other observed areas (different cities).

## 4. Traffic Control Based on Learning Agents

### 4.1. Concept of Learning Agents

The underlying controlled process can be defined as a Markov Decision Process (MDP) with the tuple (S, A, T, R), where*S is* the environment states set, *A* is the action set the controller can take, *R* is the reward function and *T* represents the transition function between states. In such a case, the RL concept can be applied with the Q-Learning (QL) algorithm as an important representative:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha(r_{t+1} + \gamma \max_{a' \in A} Q(s_{t+1}, a') - Q(s_t, a_t)), \quad (1)$$

where $Q(s_t, a_t)$ is the Q value for a state-action pair in training iteration $t$, $\alpha$ is the learning rate at which the $Q$ value is updated, $r_{t+1}$ is the reward received from the environment after a particular action was selected and $\gamma$ is the discount factor to include the impact of possible future rewards.

To train a QL-based traffic controller, all possible state-action pairsmust be visited enough times to differentiate the best action to be taken in a particular state. This leads to convergence issues because, for a good controller, the state-action pair representationmust be fine enough creating the curse of dimensionality.

## 4.2. Urban Motorways

On urban motorways two most common traffic control approaches are applied: Ramp Metering (RM) and Variable Speed Limit (VSL) [11]. In RM, vehicles from on-ramps are allowed to join the motorway main traffic flow if the occupancy or density near the on-ramp is under the critical value to postpone congestion build-up (left part of Fig. 4). Similarly, in VSL, the speed of vehiclescoming to a motorway area with increased occupancy or density approaching the critical value is decreased to resolve or at least to postpone the congestion build-up (right part in Fig. 4).

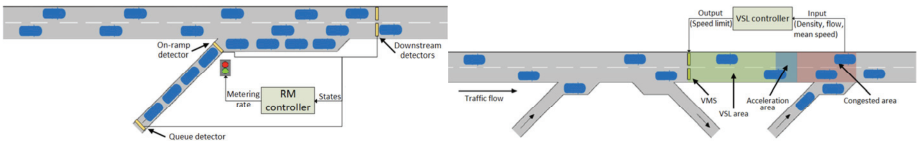


*Figure 4. Control block schemes for RM (left) and VSL (right) [11]*

To set up an agent for RM, the set of states should containthe notation about the on-ramp traffic light phase, average speed on motorway main traffic flow, and average on-ramp queue length. The action set should contain the possibility to stay in the same traffic light phase, change the phase, or turn RM off in the case of low traffic demand. The reward function should be linked to the queue length (should be minimized) and main traffic flow speed (should be maximized). When such a setup is applied on a simple motorway simulation modelwith one on-ramp, an improvement in the main traffic flow traveling time of around 10% can be expected. More details are available in [16].

To set up an agent for VSL, the sets for states and actions, and the reward function mustalso be appropriately defined. For VSL, also large oscillations of posted speed limits between control steps should be avoided. Thus, the state must include the past behavior of the main traffic flow and past actions. A good solution is to build the state vector containing two past actions (posted speed limits), and traffic density and speed in motorway areas affected by VSL. The action set should contain the allowed speed limits starting from the lowest to the highest. The reward function should positively emphasize a higher value of main traffic flow speed, minimize Total Time Spent (TTS), and penalize large oscillations of posted speed limits between consecutive control steps. With such a setup on a motorway simulation model with two on-ramps, one off-ramp and one VSL zone an improvement of 4% regarding average main traffic flow travel time including gradual change of speed limit can be expected. More details are available in [17].

## 4.3. Signalized Intersections

On signalized intersections, Adaptive Traffic Signal Control (ATSC) can be applied to alleviate congestion.The main idea of ATSC is to adapt the signal program according to the current traffic situation. Thus, RL must learn the control law for signal program adaptation. For intersection state description, queue lengths on all inbound roads can be used. The problem is the very large number of potential states in comparison to motorways negatively affecting the training convergence. However, the analysis done in [18] revealed that in the case of an independent intersection similar statescan be grouped and the same signal program can be effectively used for the whole traffic states group. Thus, by using a Self-Organizing Map (SOM) the classic RL framework can be augmented improving training convergence (left part in Fig. 5), [18]. The drawback of such a SOM-based framework is the needed apriori off-line analysis of collected queue length measurements. By using the Growing Neural Gas, combined simultaneous training of the state-action representation and control law for ATSC can be achieved (right part in Fig. 5) [19]. Thus, the control system can be implemented more easily with improved training convergence compared to the classic QL algorithm implementation. For setting the reward function, the delay difference between two action executions was used. The GNG based approach has comparable convergence and control quality despite the simultaneous state-action representation and control lawtraining. More details are available in [18, 19].

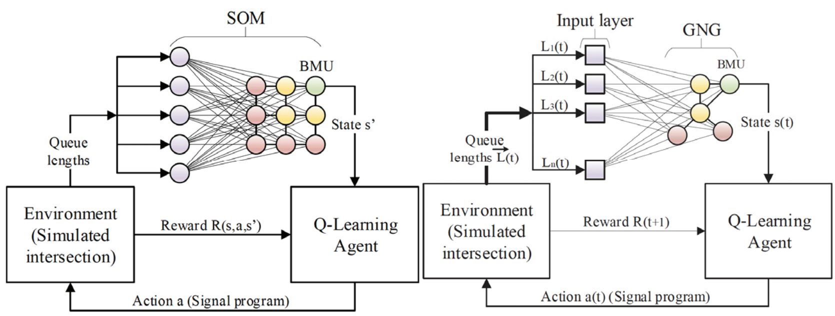


*Figure 5. Applying SOM (left) and GNG (right) for QL based ATSC [18, 19]*

## 5. Conclusion

One important application of AI in traffic technology and transport is solving the traffic control problem as a crucial ITS service. The application of expert systems as one of the most significant applications of artificial intelligence already plays a significant role in intelligent transport systems today. It has been shown that the ANFIS architecture is very useful for these applications, both in real-time applications and in traffic planning applications.

Control structures based on learning agents can cope with significant daily changes in traffic demand and update their control laws during operation evaluating the deployment of such systems. The drawback isthe needed accurate state-action representation complexity resulting with the curse of dimensionality which reduction is currently researched to improve training convergence.

Soon, a significant breakthrough in the application of AI in the field of traffic incident management is expected, [20]. Also, some new AI based applications in the area of ITS cyber security,especially for cooperative intelligent transport systems[21], are expected.

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