Applications of Soft Computing in Intelligent Transportation Systems

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Abstract Intelligent Transportation Systems emerged to meet the increasing demand for more efficient, reliable and safer transportation systems. These systems combine electronic, communication and information technologies with traffic engineering to respond to the former challenges. The benefits of Intelligent Transportation Systems have been extensively proved in many different facets of transport and Soft Computing has played a major role in achieving these successful results. This book chapter aims at gathering and discussing some of the most relevant and recent advances of the application of Soft Computing in four important areas of Intelligent Transportation Systems as autonomous driving, traffic state prediction, vehicle route planning and vehicular ad hoc networks.

1 Introduction

New trends in business, commerce or leisure have increased the demand for more efficient, reliable and safer transportation systems. This fact is claimed by different national and international institutions, such as the OECD [49] or the European Commission [20], just to name but a few. Some of the reasons behind the increasing

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importance of improving transportation systems are the offshore outsourcing of production, the adoption of just-in-time distribution systems, the tight scheduling of personal and freight activities, the broadening of international trade, the large number of people living in cities or the big amount of Green House Gases emission caused by transport.

The development of Intelligent Transportation Systems (ITS) [18] is one of the major areas of research that work in addressing these issues nowadays. ITS is a discipline that combines telecommunication, electronics, information technologies and traffic engineering methodologies to provide innovative services associated to different modes of transport as well as traffic management in order to offer the users more information and safety and to allow a more efficient and effective use of transport networks. The benefits of these systems have been successfully proved in many different transport environments [33].

Since their beginning around 1930 with the first electric traffic signals, ITS have coped virtually all facets of transport given rise to different types of systems to respond to the different problems that appear in each of those facets. Some of these types of ITS are [23]:

- *Advanced Traffic Management Systems (ATMSs)* that aim at improving traffic service quality by collecting data, supporting decision making to operators and control traffic in real-time with different systems.
- *Advanced Travelers Information Systems (ATISs)* which are design to help travelers in the different stages of their trips by providing them information in real-time about the best route to their destiny, the most appropriate schedule or transport media, etc.
- *Commercial Vehicles Operation Systems* whose objective is to increase safety and efficiency in commercial vehicles fleets, by combining different ITS technologies with the intention of improving the management and control of vehicles as well as the information available for drivers and decision makers.
- *Advanced Public Transportations Systems (APTSs)* that pursue the enhancement of the operation of public transportation media (subway, tram, bus, etc.) with the joint use of technologies from ATISs and ATMSs.
- *Advanced Vehicles Control Systems (AVCSs)* aims at assisting, alerting and taking the whole or part of vehicle driving with the aid of several in-vehicle sensors, computers and/or communication networks.

Soft Computing (SC) [75] has played a major role in the success of ITS in recent years, especially because of the bigger amount of data provided and collected from several sources by the different stakeholders involved in these systems as governments, industry and citizens [92]. ITS are an environment very appropriated to applied SC techniques because the information handle present most of the features for which SC was designed for. For example, the sensors usually present imprecision in their measures; traffic is strongly affected by factors with a high uncertainty as weather; and the decision making should take into account drivers' or other users' preferences which subject to a high vagueness and subjectivity. For these reasons, techniques such as fuzzy sets, neural networks, metaheuristics or probabilistic reasoning have been widely used by the research community in ITS.

This book chapter aims at gathering some of the most relevant and recent advances of the application of SC in ITS in order to serve as a guide for student, researchers and practitioners interested in this field. Concretely, we focus on four important areas of ITS as the AVCSs for autonomous driving, the ATISs for the prediction of the future state of the traffic, the CVOSs for the planning of routes of fleets of vehicles, as well as one of the most important key enable technologies of future ITS, vehicular ad hoc networks.

The manuscript is organized as follows. The next four sections are devoted to review the application of SC in each of the ITS areas aforementioned in order of appearance. After that, in the last section of the chapter, we discuss the main conclusions drawn from the works reviewed.

2 Soft Computing in Autonomous Driving

Autonomous driving has been one of the most benefited fields in ITS of the application of SC, since, until recently, autonomous driving remained like one of those problems that humans were able to manage better than machines [13].

The European Union has an ambitious road safety target for this decade: halving the number of road deaths between 2010 and 2020. In 2014, almost 25,700 road fatalities were reported in the EU, this is around 1% fewer deaths than reported in 2013 and 18% fewer than in 2010 [1].

Automation, and in particular digitalization of driving will change road transport in a way which will be viewed as a revolution in the field of mobility. As human error is the main reason for road traffic accidents, controlling the driving by a computer is expected to make future road transport safer and more secure. A fully automated mobility of vehicles in roads will have incredible potential impact in the society as known until now. Benefits from such total automation of the vehicles will derive in evident profits for society lowering costs and increasing safety, but also will provide deep changes in the ways people and goods move around cities.

Car sharing [8] and car pooling [82] are two examples of emerging paradigms of mobility that can deeply impact the mobility, if come accompanied by autonomous driving of vehicles involved in the business models. Some authors study social tendency of population to owning a vehicle in property, and question about the effect that autonomous vehicles will cause in social perception of owning a car [76]. Philosophical and ethical sciences are also influenced by the emergence of autonomous vehicle applications, and researchers try to answer if humans are ready for utilitarian autonomous vehicles [11]. As can be seen, not only technological but also societal and business, among other fields of research, are involved in the study of the automation of vehicles.

In one hand, both the upgrade and lowering of the sensor and equipment necessary for the processing of information needed by an autonomous vehicle to take a decision have made this field to receive interest from research groups from the entire world. In the other, methods and algorithms able to deal in each one of the stages involved in the driving of a vehicle (e.g. signal processing, decision making, control, communication or planning) are performing really well nowadays. Both equipment and methods are making nearer the day in which a fully autonomous driving is available for society.

It is known that the techniques under the topic of Soft Computing have a strong capability of learning and cognition, as well as a good tolerance to uncertainty and imprecision. Due to these properties they can be applied successfully to problems derived by the driving of a vehicle. Methods associated to the field of Soft Computing have been naturally used by researchers to take steps through the development of autonomous vehicles.

In the remainder part of this section, some of the most relevant applications of Soft Computing to the field of autonomous vehicles are discussed. These applications are structured according to the main Soft Computing technique involved, concretely, fuzzy logic, genetic algorithms and neural networks.

2.1 Fuzzy Logic in Autonomous Driving

Due to the ability of representing expert knowledge in the form of simple and legible rules, fuzzy logic has been broadly used in the field of autonomous vehicles, mainly in the development of control algorithms. In this case, control of a complex nonlinear system can be expressed in the form of a set of simple fuzzy rules (e.g. if speed is too high, then press brake). Fuzzy based methods are specially indicated when we try to emulate human control actions, such as human car driving [59].

Examples of the use of fuzzy rules for the control of the elements of an autonomous vehicle can be found in the recent literature in large amount of examples. In [64], Rodriguez-Castao et al. used a Takagi-Sugeno-Kang fuzzy system for GPS based autonomous navigation of heavy vehicles at high speed. Other example can be found in [22], where Faddel et al. used a fuzzy system to manage the controller for electric vehicle charging. The steering control of autonomous vehicles has received important attention from researchers in fuzzy logic, examples of such interest are [5], where the authors proposed an autonomous platooning system for trucks, including steering control, in order to increase in traffic capacity. Motion planning has been another topic where fuzzy logic has been applied. For instance, in [37], Kala and Warwick implemented decision making over autonomous vehicle maneuvering. Pedals control by fuzzy logic has been also tackled in several works, as [51] or [34].

2.2 Metaheuristics in Autonomous Driving

Metaheuristics, specially genetic and evolutionary algorithms, have been extensively used, as optimization methods in the field of autonomous driving. Their main objective has been the tuning of control systems, decision making and improvement of the efficiency of the overall traffic. In conjunction with fuzzy logic, as the way of representing knowledge, these algorithms have been extensively used for optimizing the distribution of membership functions, rule base or both, under the paradigm of the genetic fuzzy systems.

In [19], Du et al. used a genetic algorithm to optimize a model predictive controller for the simultaneous control of the steering and pedals of an autonomous vehicle, taking the comfort of the passengers as an objective to optimize. A path planning and scheduling method for fleets of autonomous vehicles was proposed in [79]; in this work, Xidias et al. used a genetic algorithm to obtain a near optimum solution for a problem resulting of combining both (planning and scheduling) ones. A multi-objective genetic algorithm was used by Onieva et al. in [52] in order to generate speed profiles for autonomous vehicles to follow in order to cross an intersection where no cooperation among vehicles is possible. Finally, parking trajectories have also been candidates to be optimized by evolutionary algorithms [91].

2.3 Neural Networks in Autonomous Driving

Neural networks (NNs) provide a set of qualities that makes them extremely precise for the representation of complex non-linear systems. They have been used in the field of autonomous vehicles, in one hand, for the control of the actuators of the vehicle, but also for the processing of the high amount of data received by the vehicle, in particular under the field of computer vision.

Recently, with the explosion of deep learning paradigm [66], researchers have defined a new framework where all the information available is used to train models, which are increasing in accuracy as new elements are fed into the NN [15]. They have been applied by a large number of researchers to the processing of visual information captured by autonomous vehicles. In [36], Jia et al. used deep neural networks to provide precise obstacle detection in front of an autonomous vehicle, as well as to segment obstacles and infer their depths. A convolutional NN is used in [88] by Yang et al. to classify roads signs in a hierarchical way, obtaining both the subclasses within each superclass exposed in a picture. In combination with fuzzy logic, the work by Barman et al. [7] presented a fuzzy-NN to guide an unmanned vehicle for maintaining traffic rules to reach its goal and avoid obstacles. Examples of control of actuators at a low level by means of NNs can be found in [17] for lateral, and [58] for the longitudinal control of autonomous vehicles.

3 Soft Computing in Traffic State Prediction

According to the Eurobarometer 2014 about the quality of the transportation, the preferred mode of transport in a typical day is the car, well above from urban public transport. This issue, added to the fact that vehicles per capita have been increased in the last 10 years, has raised the efficiency of the transport to the level of fundamental condition, especially in big cities. For these reasons, road trips are a key point inside ITS, due to the importance in daily life not only for people but also for transportation companies. Inside this subject, one field where different techniques are being used during the last years with a high impact and reliable performance is the prediction of the traffic state in freeway and urban scenarios. One of the principal challenges in this field is to predict, with a certain level of confidence, possible traffic jams in a short-term horizon. The principal advantage of the successful prediction of traffic jams is the adaptation of decision making in the exact moment when different events that may affect traffic, as for example accidents, occur. Another advantage is the capability of calculating not only the travel time but also of planning the route to follow before its beginning. If the user knows the probability of finding a traffic jam in its route, he/she can avoid it by changing the route before or even during the journey. In a general way, the successful prediction of traffic jams can lead to the decrease of travel time, the reduction of CO_2 emissions as well as fuel consumption, or the decrease of acoustic contamination in urban and freeway environments.

Following the same guidelines of the previous section, some relevant applications of Soft Computing in traffic state prediction are reviewed. Concretely, the application of the three components of Soft Computing most commonly used in this topic as neural networks, fuzzy logic and probabilistic reasoning.

3.1 Neural Networks in Traffic State Prediction

In the last years, traffic congestion prediction is one of the fields where NNs have been widely used, as can be seen in literature. For example, in [42], Kumar et al. applied a NN to predict traffic congestion using historical traffic data. Volume, speed, density, and both time and day of the week were used as input variables. The model was validated using rural highway traffic. Another case was presented in [50] by Oh et al., where Gaussian mixture model clustering is combined with a NN to create an urban traffic flow prediction system. The system forecasts traffic flow by combining road geographical and environmental factors with traffic flow properties obtained by the use of detectors. Another type of NNs, called Back Propagation NN (BPNN) is used to forecast campus traffic congestion level in [90]. The results are compared with a Markov model, and the BPNN achieved higher accuracy and more stable performance.

In [41], Koesdwiady et al. used a deep belief networks to enhance prediction accuracy using weather conditions. The study had two objectives: to investigate a correlation between weather parameters and traffic flow, and to improve traffic flow prediction accuracy. The data used for this paper was originated from San Francisco Bay area of California. A Big Data-based framework was adopted in [68] by Soua et al. to address the problem of short-term traffic flow prediction. Deep belief networks are used to independently predict traffic flow using historical traffic flow and weather data, and event-based data.

3.2 Probabilistic Reasoning in Traffic State Prediction

Authors of [4] presented an hybrid approach of parametric and nonparametric methods such as an ensemble of Kalman Filter and NNs in order to improve the travel time prediction of journeys that starts from 15 to 30 min in the future. Kalman Filter was combined with ARIMA in [80], where the ARIMA model is built using historical traffic data. After that, the model is integrated with a Kalman Filter to construct a road traffic state prediction algorithm. Four road segments in Beijing were adopted for the case studies accomplished.

In [24], Fusco et al. hybridized Bayesian networks and NN to create short-term prediction models using as data the link speeds recorded on the metropolitan area of Rome during 7 months. Other example where Bayesian networks are applied to short-term traffic prediction was presented in [81]. In the mentioned paper, traffic flow is predicted using a Bayesian multivariate adaptive-regression splines model. Data is collected from a series of observation stations along the freeway Interstate 205 in Portland, USA, and used to evaluate the performance of the model. Results were compared with different methods, as ARIMA, seasonal ARIMA, and a Kernel method Support Vector Regression.

3.3 Fuzzy Logic in Traffic State Prediction

As mentioned above, fuzzy logic allows to process imprecise information using IF-THEN rules, which helps to the interpretation of the final model. One of the most used and known types of fuzzy systems are Fuzzy Rule Based Systems (FRBS), which can be divided into Mamdani and Takagi-Sugeno-Kang (TSK) systems. Besides, another kind of systems, based in the previous ones, are called Hierarchical FRBS (HFRBS). This class of systems counts with several FRBSs, which are joined in a way that the output of one of them is connected to the input of another one. Depending of the structure of the hierarchy, those systems can be divided into parallel, serial, and hybrid [9].

In traffic congestion prediction, those systems have been used in [93, 94] to develop a congestion prediction system employing a large number of input variables. In these papers, a Steady-State GA is applied to tune the different parts of the FRBSs. A related work is presented in [45], where Lopez-Garcia et al. used a hybrid algorithm that combines GA and Cross Entropy method to tune a HFRBS in order to predict congestion in a freeway in California with time horizons of 5, 15, and 30 min. An extension of that work is presented in [46], where state-of-the-art techniques are compared with the results obtained by the tuned HFRBSs in different traffic congestion datasets. Finally, another interested paper in this topic was presented in [53] Onieva et al. where the authors compare the performance of several Evolutionary Fuzzy and Crisp Rule Based methods for traffic congestion prediction.

4 Soft Computing in Vehicle Route Planning

Other field in which soft computing techniques have demonstrated an outstanding performance is vehicle route planning or vehicle routing problems. Nowadays, route planning is a widely studied field in which the most used and well-known problems are the Traveling Salesman Problem (TSP) [43], and the Vehicle Routing Problem (VRP) [44], being the focus of a big amount of studies in the literature.

The reasons for the importance and popularity of this kind of problems are both scientific and social. On the one hand, most of the problems arising in this field have a great complexity since they belong to NP-Hard class. For this reason, their resolution supposes a major challenge for the scientific community. On the other hand, routing problems are usually built to address real world situations related to logistics, transportation, electronics, robotics, etc.

The first part of this section is focused on metaheuristics, whose application in the resolution of these optimization problems has been very successful. The second part revolves around the use of fuzzy logic in routing problems, describing some relevant works published in the last years.

4.1 Metaheuristics in Vehicle Route Planning

Metaheuristics have been widely used for the solving of routing problems in the last decades, becoming the state-of-the-art in the resolution of many of the variants of these problems. One of the first metaheuristics applied in this context was Simulated Annealing (SA) [74]. For example, in [47], Malek et al. presented a serial and parallel SA for solving the TSP. Other example of the application of this technique for route planning is the work published by Chiang and Rusell [16], in which the VRP with Time Windows is solved using a SA. More recently, Baos et al. developed a parallel variant of SA, called Multiple Temperature Pareto SA in [6], to also solve the VRP with Time Windows with very successful results. Another well-known stochastic local search, Tabu Search (TS), has been also frequently used for solving route planning problems. A recent work on this topic is the one presented by Escobar et al. in 2014 [21], in which they proposed a hybrid granular TS for tackling the challenging Multi-Depot VRP. Briefly explained, the proposed method considers different neighborhoods and diversification strategies, with the aim of improving the initial solution obtained by a hybrid procedure. The Variable Neighborhood Search (VNS) has also demonstrated its efficiency in this area. An interesting example is the work presented in [14], in which Carrabs et al. proposed a VNS for solving a multi-attribute version of the TSP: a Pickup and Delivery TSP with LIFO Loading. More concretely, the authors of this paper introduce three new local search operators, which are then embedded within a VNS. In a more recent publication, Sarasola et al. [65] developed a VNS for facing a stochastic and dynamic VRP. This version of the VRP contemplates two different features. The first one is stochastic demand, which is only revealed when the vehicle arrives at the customer location. The second feature is the dynamic request, meaning that new orders from previously unknown customers can be received and scheduled over time.

Furthermore, evolutionary methods have also shown a great performance for this sort of problems, being Genetic Algorithms (GA) one of the most successful ones. The work presented by Vidal et al. in 2013 is an example of this fact [77]. In this research, a hybrid genetic algorithm with adaptive diversity management is implemented for tackling the VRP with time windows. Another example is the survey paper published by Karakatič and Podgorelec in 2015 [39], which collects some of the most important works focused on the application of the GA to the multi-depot VRP.

Additionally, since the appearance of GA in the early 1970s, a wide variety of nature-inspired metaheuristics have also appeared in literature. Some of these recently proposed methods are the Firefly Algorithm (FA) and the Bat Algorithm (BA). The FA was proposed by Yang in 2008 [84]. This meta-heuristic has been applied to a wide range of optimization fields and problems since its proposal [87], and it has also shown a promising performance for routing problems. In [35], for example, Jati and Suyanto presented the first application of the FA for solving the TSP. In order to do that, authors adapt the FA, which was firstly proposed for tackling continuous problems, providing it with an evolutionary and discrete behavior. Another interesting example of application is the one presented in [3] by Alinaghian and Naderipour, in which a hybrid version of the FA is proposed to solve a time-dependent VRP with multi-alternative graph, in order to reduce the fuel consumption. The developed hybrid version of the FA is a Gaussian Firefly Algorithm. The most interesting part of this paper is the real-world use case that authors presented, focused on a distribution company, established in Esfahan, Iran. Additionally, in [56] Osaba et al. also shown that the FA is able to face complex routing problem, such as the asymmetric and clustered VRP with simultaneous pickup and deliveries, variable costs and forbidden paths. Finally, in [54], the same authors presented a evolutionary discrete FA with a novel operator to deal with VRP with time windows with successful results.

Regarding the other nature-inspired method mentioned above, the BA, it was proposed by Yang in 2010 [85]. As can be read in several surveys [86], the BA has been successfully applied to different optimization fields and problems since its proposal. Focusing in routing problems, several recent papers have shown that the BA is a promising technique in vehicle route planning. For example, in [70], Taha et al. presented an adapted version of this algorithm for solving the well-known Capacitated VRP. The Adapted BA developed in that study allows a large diversity of the population and a balance between global and local search. Zhou et al. addressed the same problem in [95]. In that paper a hybrid BA with path relinking is described. This approach is constructed based on the framework of the continuous BA, in which the greedy randomized adaptive search procedure and path relinking are effectively integrated. Additionally, with the aim of improving the performance of the technique, the random subsequences and single-point local search are operated with certain probability. In [55], Osaba et al. presented an improved adaptation of the

BA for addressing both symmetric and asymmetric TSP. The results shown that the improved version of BA could obtain promising results, in comparison with some reference techniques, such as an evolutionary simulated annealing, a genetic algorithm, a distributed genetic algorithm or an imperialist competitive algorithm.

We want to highlight that the meta-heuristics referenced in this section form a small part of all different approaches that can be found in current literature. We are aware that many other interesting and efficient techniques are available in the scientific community, such as the Harmony Search [27], or Gravitational Search [61, 62], which also show a good performance when they are applied to routing problems. Additionally, many additional classic methods have also shown a great performance for this kind of problems, such as the Particle Swarm Optimization [89], the Ant Colony Optimization [63] or Large Neighborhood Search [60].

4.2 Fuzzy Logic in Vehicle Route Planning

The use of fuzzy systems is also an important topic in the field of vehicle routing problems. In real situations, these problems are susceptible to suffer imprecision or uncertainty in their data. Many works in literature show that one of the most successful ways to tackle with this uncertainty and imprecision in the information available when solving vehicle route planning problems, it is the use of fuzzy logic.

In this way, we can find interesting studies in the literature, such as the one presented in [29], in which Ghannadpour et al. proposed a multi-objective dynamic vehicle routing problem with fuzzy time windows. In this research, authors not only describe the problem, but also the main real-world applications that it could have. The constraints related with travel times and user satisfaction are some of the most subject to uncertainty and imprecision. Apart from the previous work, this type of imprecision is modelled in other studies such as the one presented by Tang et al. in [71], in which a VRP with fuzzy time windows is proposed and solved using a two-stage algorithm which decomposes the problem into two subproblems. An additional example of this trend is the work proposed in [28], in which a multi-objective dynamic VRP with fuzzy travel times and customers' satisfaction level is presented. Specifically, the customers' satisfaction level is considered in the route planning of vehicles by using the concept of fuzzy time windows. Additionally, the dynamic solving strategy proposed is based on a genetic algorithm, and its performance is evaluated on various test problems generalized from a set of static instances in the literature. Other interesting application of fuzzy logic for vehicle routing problems are the works presented in [12], where Brito et al. proposed a variant of the close-open VRP with fuzzy time windows and fuzzy vehicle capacity, and [72], where Torres et al. solved a variant of the Truck and Trailer Routing Problem where the imprecision in the capacity of the truck and the trailers is modeled by fuzzy logic.

5 Soft Computing in Vehicular Ad-Hoc Networks

Vehicular Ad-Hoc Networks (VANETs) are communication networks in which the nodes are vehicles [32]. This field has attracted the attention of the scientific community, automobile industry and institutions worldwide because of the huge number of innovative applications they can enable [57]. Among the areas of application, some of the most relevant are: security (warnings about emergency break, collision at intersection, line shift, etc.); leisure and entertainment (multimedia content download, nearby points of interest, etc.); traffic management (virtual traffic lights, limited access zones, electronic tolls, etc.); and driver assistance (remote diagnosis; efficient and eco-driving; etc.). The communications that take place within VANETs can be classified in Infrastructure-to-Infrastructure (I2I), Infrastructure-to-Vehicle (I2V), Vehicle-to-Infrastructure (V2I) and Vehicle-to-Vehicle (V2V) depending on which agent is the transmitter and the receptor.

VANETs are an especially complex environment because of the high dynamism in the movement of the vehicles, communication failures, different driver profiles, high variability of nodes and interconnections, etc. For this reason, data handled in VANETs is subject to imprecision, uncertainty and vagueness which make it an excellent field for the application of Soft Computing techniques. This section is devoted to review some of these applications. Concretely, the next subsections will show, in this order, applications in VANETs of three components of Soft Computing as metaheuristics, fuzzy sets and neural networks.

5.1 Metaheuristics in Vehicular Ad-Hoc Networks

In the context of VANETs, several complex optimization problems appear, in which metaheuristics have shown to be an excellent tool to solve them. One of the first works in which metaheuristics were applied to VANETs can be found in [26]. Here, Garcia-Nieto and co-authors proposed the used of these techniques to optimize the File Transfer Protocol Configuration. Concretely, they optimized the parameters of the Vehicular Data Transfer Protocol, which operate over the transport layer protocol of VANETs, in order to allow end-to-end communications. To address this problem, they test five different metaheuristics over two scenarios that simulated urban and highway environments. The authors concluded that the metaheuristics reduced the transmission time in a 19 and 25.43% in urban and highway scenarios, respectively, when they were compared to the configuration provided by a human expert. A similar approach was followed by the same authors in [73]. In this case, the five metaheuristics mentioned before were employed to find the optimal configuration of the Open Link State Routing protocol for VANETs. The results showed again a significant improvement in terms of Packet Delivery Ratio (PDR), network routing load and End-to-End Delay (E2ED) in comparison to standard and expert configurations.

Another optimization problem from VANETs that has been addressed with metaheuristics is multi-cast routing. Souza et al. presented in [69] a tree based multicast routing protocol called MAV-AODV. Here, the Ant Colony Optimization's pheromone mechanism is used to establish a quality measure of the stability of the routes. The new method was tested over a simulated Manhattan scenario and compared with the MAODV protocol. MAV-AODV obtained a better performance than MAODV in terms of E2ED, overhead and PDR. Other example of routing protocol inspired in metaheuristics was presented in [10]. This unicast and multipath protocol, called HyBR, used two types of routing procedures: a topology-based and a geographic-based routing procedure for high and low density scenarios, respectively. The first one was inspired in the working of bee swarm optimization whereas the second one used a genetic algorithm to optimize the route between the origin and the destiny. The experimentation was done over high density and a low density scenarios and the performance measures considered were the average E2ED, PDR and normalized overhead load. HyBR outperformed AODV and geography-based routing protocol (GPSR) in the first two measures but not in the last one.

A more recent application of metaheuristics in VANETs is given by Masegosa et al. in [48]. This work is focused on information dissemination from a central server to vehicles by means of Virtual Infrastructures (VIs). The selection of the nodes of the VI is modelled as a covering location problem and it is solved by means of a genetic algorithm. The main challenge for metaheuristics in this environment was the short response time imposed by the latency requirements of some VANET's applications. The experimentation over a real scenario with 45 vehicles indicated that the proposal outperforms another state-of-art method based on a deterministic greedy strategy, called NAVI.

5.2 *Fuzzy Logic in Vehicular Ad-Hoc Networks*

Fuzzy set theory has been also applied in different areas of VANETs. For example, in [30], Abdel Hafeez et al. presented a Cluster Head (CH) selection mechanism that made use of a fuzzy inference system. CH selection is one of the main challenges of cluster-based medium access control protocols, whose aim is to improve the access and capacity of the network among other aspects. The previous mechanism elected the CHs dynamically and taking into account a stability criteria. The fuzzy inference system was used to predict the future position and speed of all cluster members using as input the inter-vehicle distance and speed. The procedure proposed outperforms CMCP [31] and APROVE [67] protocols.

Another fuzzy inference system was presented in [78] to design a multi-hop broadcast protocol, named FUZZYBR. In a more specific way, the fuzzy inference system was employed to select the relay nodes considering variables with a high degree of imprecision and uncertainty as the inter-vehicle distance, mobility and signal strength. The evaluation of the methods was done over simulated freeway and street scenarios, and the proposal was compared with other broadcast protocols as

Flooding, Weighted persistence, MPR and Enhance MPR. The results confirmed a significant performance advantage of FUZZYBR over the mentioned protocols in terms of PDR, E2ED and number of messages per data package. In [25], Galaviz-Mosqueda et al. utilized FUZZYBR and another multi-hop broadcast protocol based on fuzzy inference systems, and called RLMB, to test the use of genetic fuzzy systems. The motivation of the authors was to adjust the membership functions of the fuzzy rules of the two protocols by means of a genetic algorithm, in order to obtain a better performance than the one with expert tuning. The results confirmed their hypothesis, and the two versions of FUZZYBR and RLMB automatically tuned with the genetic algorithm significantly improved the performance of the counterparts heuristically configured by humans.

Fuzzy control was also applied in VANETs to adapt beaconing rate to the changes in traffic density that usually occur along time. This mechanism, called ABR, was proposed in [96] where the authors developed a method in which a rule-based system adapted the frequency of beacon broadcasting taking into account the percentage of vehicles traveling in the same direction and the emergency status of vehicles. The simulations showed how this method reduced the beaconing load at the expense of cooperative awareness between vehicles.

5.3 Neural Networks in VANETs

One of the first works that suggested the application of NNs to VANETs can be found in [40]. In this paper, the authors aimed at demonstrating the benefits of VANETs on traffic safety, and concretely for designing an Accident Prevention Application (APA). To this end, they proposed, in a first stage, the use of a Markov Reward Process to estimate the expected time until an accident will happen, taking into account the traffic states observed so far; and in a second stage, the use of NNs to make these estimations when there are unobserved traffics situation. To this end, the NNs should have been trained with known pairs (state, expected time). The authors claimed that, in this way, they provided the basis for the analysis of VANETs and their impact on traffic safety.

In a more recent paper [83], Yang et al. combined ANN and VANETs to develop a short-term average-speed forecast and adjustment approach to improve gas consumption, decrease CO_2 emissions and reduce travel time. In the proposed method, a Traffic Information Center (TIC) collected average speed from vehicles and road side sensors through VANETs. Then, the TIC trained a NN with average speed, weather information and traffic flow to predict the average speed. The predicted speed was then sent to the CH that adjusted the prediction according to the observed speed. The simulations done showed an important improvement in the accuracy of the average-speed predictions when the system was compared versus a hybrid approach.

Another important issue in VANETs handled with NNs is security and vulnerability, given that VANETs are even more exposed than other similar networks. A good example of this application can be found in [2], where the authors employed

NNs to build an Intrusion Detection System (IDS) to prevent Denial of Services (DoS) attacks. Concretely, the aim of the NN was the real-time detection of malicious vehicles in order to isolate them from the network. With this purpose in mind, the authors generated data for normal and malicious vehicles through simulations. From this data, they extracted relevant features and a pre-processed dataset that it was used to train the NN. The experimentation showed that the system obtained an error rate of 2.05%, confirming its effectiveness. Other example of the application of NNs for security in VANETs has been recently presented in [38]. The authors of this work developed a Deep NN (DNN) for an IDS to secure in-vehicular networks that use the CAN protocol. Concretely, the proposed IDS considered a scenario in which malicious data-package are injected into the in-vehicle CAN bus. The DNN was trained with labeled (i.e. normal or attack) and preprocessed CAN packets to extract features that model the statistical behavior of the network. In the detection phase, each CAN packet was pre-processed and passed to the trained DNN to make the binary decision. The experimentation demonstrated that the approach obtained a 98% detection ratio in real-time response to attacks.

6 Discussions

In this book chapter we have presented an overview of application of SC to four important areas of ITS: autonomous driving, traffic state prediction, vehicle route planning and VANETs. Our overview has shown that SC techniques are an effective and efficient framework to deal with many of the problems that arise in those areas and therefore, to develop better performing ITS.

The main reasons behind the success of SC in the four ITS areas aforementioned is associated with the recent trend in ITS to follow a data-driven approach; and the inherent tolerance of SC techniques to deal with the imprecision, uncertainty and vagueness, omnipresent in the information handled in this complex environments, and their ability to provide cost-effective solutions.

To finish, we would like to point out that the emergence of new ITS technologies such as autonomous cars, electric vehicles, more advance VANETs or Unmanned Aerial Vehicles will probably boost a shift paradigm, along the next decade, in the way in which goods and persons are transported nowadays. SC plays and will play a major role in this shift so we augur a great future for the application and development of SC techniques in this field.

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