

© 2021 IEEE. Personal use of this material is permitted. Permission from IEEE must be obtained for all other uses, in any current or future media, including reprinting/republishing this material for advertising or promotional purposes, creating new collective works, for resale or redistribution to servers or lists, or reuse of any copyrighted component of this work in other works.

# A Decision Support Model for Transportation Companies to Examine Driver Behavior

Marjana Čubranić-Dobrodolac, Libor Švadlenka Goran Z. Marković and Momčilo Dobrodolac

**Abstract**—The entire society, and particularly the transportation companies, have the interest to improve traffic safety. Besides more than 3,000 lost lives on the roads every day, there are significant financial consequences of road traffic accidents (RTAs). The purpose of this paper is to design an efficient model for providing information about driver propensity for RTAs based on assessing their personality traits. This is achieved by creating a fuzzy inference system (FIS) where inputs are the scores from the implemented psychological instruments and output is the number of RTAs experienced by a driver. To adjust the functioning of FIS to the empirical data, a Bee Colony Optimization (BCO) metaheuristic is applied. In this optimization procedure, we test three approaches for defining the variables of initial FIS and compare their performance. Simulation results show the differences between the considered approaches, and generally, very promising achievements of the proposed algorithm. The best-found FIS reached a 36% improvement of the objective function compared to the starting FIS. This FIS can be used, *inter alia*, as a decision-making tool in recruitment procedures for professional drivers to assess their propensity for RTAs, by that saving the lives of people and reducing the costs of the companies.

**Index Terms**—Decision-making, fuzzy inference system, bee colony optimization, driver behavior, road traffic accidents

## I. INTRODUCTION

ROAD safety policies aim at defining certain measures to reduce the number and consequences of road traffic accidents (RTAs). Although the knowledge about RTAs is increasing, there are still many lives lost on the roads. This is evident even in the most developed countries. For example, more than 90 people die in the RTAs in the United States every day [1], or more than 70 in the European Union [2]. On the other hand, RTAs cause considerable financial losses, not just for the involved persons, but also for their employers, insurance companies, and the governments. Few studies measure the exact values. Based on the research carried out in Belgium, the unit cost per RTA amounts to €2 355 763, €850 033, €34 944 and €2571 for fatal, serious, slight injury and property damage RTAs, respectively [3]. Calculating the costs of RTAs at the city level, García-Altés and Pérez [4] assessed that the total yearly costs in Barcelona were €367 million.

Particular attention in the prevention programs should be placed on heavy vehicles because they can cause more serious losses of lives and property in RTAs, as they can carry much more freight or passengers than light vehicles [5]. Work-related driving safety, or fleet safety, demands the management of fleet vehicles, and more importantly, the management of individuals who drive fleet vehicles [6]. A significant part of this management that shapes the future of a transportation company is related to a recruitment procedure for professional drivers. To develop the most efficient programs, decision-makers permanently need to analyze the causes of accidents and search for the models of RTAs prediction. In practice, the professional driving recruitment department puts attention to the driving skills of a candidate. However, the individual with good driving skills is not necessarily a safe driver. The reason lies in the fact that the personality and attitudes toward safety significantly contribute to this phenomenon. Therefore, in the recruitment procedure, there is a need to examine, besides physical abilities and competency, the propensity for RTAs based on psychological traits and safety attitudes. A possible model of this kind is proposed in [7] where driver behavior is modeled by the fuzzy inference system (FIS). We are preliminarily encouraged by the idea that the FIS proposed in [7] can be further improved in sense of achieving better solutions. This means that the results of FIS can be better adjusted to the collected empirical data and hence, its functioning would be more suitable to the realistic conditions. This is precisely one of the research gaps and motivation to carry out the research presented in this paper. An additional motivation is the fact that, by reviewing the literature, we did not find examples of modeling driver behavior by FIS where the subjective indicators are used; in all other cases, the applied indicators can be measured by certain technical devices.

The considered FIS has four input variables and one output variable. The input variables represent the scores obtained from four psychological instruments and the output variable is the number of RTAs that a driver experienced. Therefore, this paper aims to perform an optimization of FIS that would be a decision-making tool for assessing the driver propensity for RTAs. The mentioned optimization procedure aims to fine-tune the parameters of FIS in a way to achieve the performance that corresponds as precisely as possible to the collected empirical

Manuscript received June 8, 2021; revised July 28, 2021; accepted August 2, 2021. Review of this manuscript was arranged by Department Editor Dilek Cetindamar. (Corresponding author: Momčilo Dobrodolac.)

Marjana Čubranić-Dobrodolac, Goran Z. Marković, and Momčilo Dobrodolac are with the Faculty of Transport and Traffic Engineering,

University of Belgrade, 11000 Belgrade, Serbia (e-mail: marjana@sf.bg.ac.rs; g.markovic@sf.bg.ac.rs; m.dobrodolac@sf.bg.ac.rs).

Libor Švadlenka is with the Faculty of Transport Engineering, University of Pardubice, 53210 Pardubice, Czech Republic (e-mail: libor.svadlenka@upce.cz).

data. In other words, the goal is to minimize the objective function which measures a cumulative deviation between the results of FIS and data collected for each of the 305 drivers who participated in this research.

To optimize the FIS performance, various techniques can be used. Since this is an extremely complex task of combinatorial optimization in sense of the enormous number of possible solutions, some of the approximate methods would be an expedient tool to use. In recent years, various swarm intelligence algorithms are developed. Here, we apply a Bee Colony Optimization (BCO) metaheuristic to optimize the FIS. By analyzing the literature from the field of optimization algorithms, it can be seen that BCO gives very competitive results comparing to some other techniques. In [8] the author applied BCO to optimize 50 numerical test functions and compared the results with the performance of a Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), and Artificial Bee Colony (ABC). The obtained results indicate that BCO mostly generates the same or better solutions. Marković [9] compared BCO with DE and PSO while solving the wavelength converters placement problem and demonstrated that BCO achieved not just high-quality solution, but significantly outperforms the computational efficiency of other considered approaches. In [10], [11] it is shown that BCO gives better solutions than DE or heuristic algorithms Max-Profit and first-come-first-served (FCFS). The authors of [12] performed 41 numerical experiments showing that the BCO generated high-quality results that are very competitive with GA and Lagrangian relaxation concerning both solution quality and computational performance. The results of the mentioned studies motivated us to test the BCO approach in this paper, more specifically its improving version – BCOi that is for the first time applied in [13] for FIS parameters optimization. However, the research gap noticed here is that the algorithm proposed in [13] test also unwanted FIS structures by that impairing the execution performance. To solve this problem, in this paper we propose a new strategy within BCO related to the selection of points to be tested during one iteration of algorithm execution. This results in a dynamic tuning of possible domains of tested variables in each change, which leads the artificial bees to find possibly better solutions more efficiently.

The procedure of FIS performance optimization implies setting an initial solution. Many authors start the optimization from an intuitively or randomly generated FIS. This can be seen as another research gap. In this paper we consider three approaches to set an initial FIS in the process of optimization and compare their performance in a sense of found solution goodness. These approaches differ in the way how input variables are defined.

Therefore, the main contributions of this paper include that: (1) Driver behavior is efficiently modeled by the FIS that calculates a driver propensity for RTAs based on assessing their personality traits. This can be used in many areas, such as educational procedures for improving traffic safety according to personality characteristics of the driver, or as a decision-making tool in recruitment procedures for professional drivers;

(2) A new strategy for determining the domains of search within BCO metaheuristic is devised in the case of FIS performance optimization; (3) By testing three approaches, we contributed to solving the task of designing a proper initial solution in the optimization of FIS performance.

A more concrete explanation of the stated contributions is given in Section 2, where the methodology of research is described together with the literature review from the considered fields. Calculations and simulation results are presented in Section 3. Finally, we conclude with a description of the benefits of the findings presented in this paper.

## II. METHODOLOGY AND RELATED WORK

The methodology of research covers several areas. Firstly, the psychological instruments to assess the drivers' personality traits were considered. These instruments were chosen in a way to describe as accurately as possible the driver propensity for RTAs. Further, a survey was carried out to collect data about drivers. The third methodological issue relates to the design of a FIS to be a starting point for the optimization procedure. Finally, the optimization of FIS is performed by the BCO metaheuristic. As a result of the optimization procedure, there is a FIS that represents a model for explaining driver behavior with minimal deviations from the empirical data. A research configuration is shown in Fig. 1.

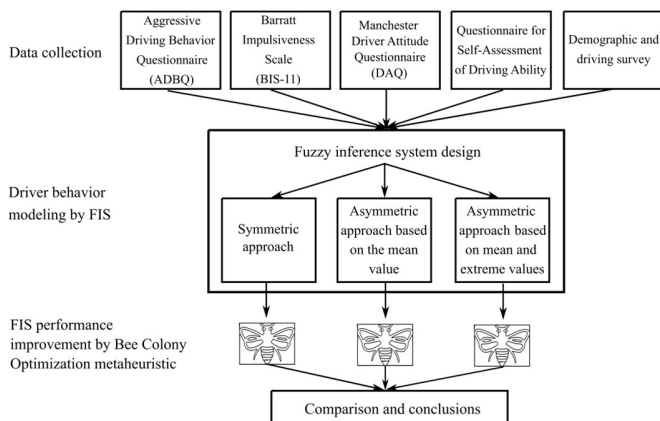


Fig. 1. Research configuration

### A. Preliminaries concerning driver behavior modeling

There is a generally accepted pattern about the classification of RTAs causes. They can be classified into three general groups [14]: human factors, mechanical factors related to the vehicle, and environmental factors and road conditions. By reviewing the literature, human errors are recognized as the far most common influential factor causing more than 90% of RTAs [15]. The examples of the human factor influence in the occurrence of RTAs are numerous. One of the common terms used here is careless driving. It is a driving style below the expected by a responsible and careful driver. A list of unsafe driving maneuvers can be extensive: illegal lane changes, speeding, excessive honking, absence of turn signals, drowsy driving, etc. The offense that is even more serious is reckless driving. It represents an intentional or wanton disregard for the

traffic safety rules such as aggressive driving, significant speeding, racing at public roads, tailgating, and many other risky actions that endanger the own or the lives of others.

A common cause of RTAs is also distracted driving, especially in the population of young drivers [16]. This involves communication with the passengers, using a mobile phone or other devices, eating or drinking behind the wheel, grooming, or application of makeup. Further, operating a vehicle while impaired by alcohol or drugs is a serious offense that can lead to the occurrence of RTAs. By analyzing the police reports about 17,945 tested drivers in urban areas and 19,507 in rural areas, the authors of [17] concluded that the motorcyclists represent a category with the highest share of driving under the influence.

It is proven that the drivers who do not respect the traffic rules in one segment, usually do not behave properly also in some other segment. For example, drivers in Serbia are forbidden to talk on the phone while driving, except when using a hands-free device. In [18] it is shown that the participants who violate this rule, are prone to drive under the influence of alcohol as well, especially the group of drivers who experienced more than three RTAs in their driving experience. This points to the conclusion that the human factor as a cause of RTAs and general driver behavior can be explained to a large extent by the corresponding psychological traits, as confirmed in [19]-[22].

To model driver behavior, in this paper, we use four psychological instruments, which were statistically proven to be good predictors of involvement in RTAs [23]. Further, the same instruments were combined with the fuzzy logic to form a model for assessing driver propensity for RTAs in [7]. The fuzzy logic is particularly convenient to be used in this kind of model because a measurement or assessment of psychological traits always contains a certain level of fuzziness and approximations even in the cases where the scores from psychological instruments are exactly expressed with crisp values.

### *B. Collection of data*

To collect data, two types of questionnaires are used. The first utilizes four psychological instruments for assessing driver behavior and the second involves a demographic and driving survey. Four psychological instruments considered in this research are the Aggressive Driving Behavior Questionnaire (ADBQ), the Barratt Impulsiveness Scale (BIS-11), the Manchester Driver Attitude Questionnaire (DAQ), and the Questionnaire for Self-Assessment of Driving Ability. The demographic and driving survey completed by the participants provides a range of information; however, for this paper, the main purpose is to obtain information about the number of RTAs in which each participant was involved.

The final database that is used for the design of FIS and further for its optimization contains data on the score each participant obtained for each of the psychological instruments and the number of RTAs per participant. The scores from psychological instruments are considered as input variables of FIS and the number of RTAs as output.

The ADBQ was created by Mouloua, Brill, and Shirkey [24].

Their idea was to design an instrument with good predictive power considering aggressive situations that are typical in driving. The instrument contains 20 questions. The participants were asked to assess the likelihood of manifestation of aggressive driving using a 6-point Likert scale. Results were given in the range of 1 = never to 6 = almost always. Based on the answers, a score from the ADBQ could range from  $20 \times 1 = 20$  to  $20 \times 6 = 120$ .

The second implemented psychological instrument is the BIS-11. This instrument is used for the assessment of impulsivity while driving. A version of BIS-11 designed by Patton, Stanford, and Barratt [25] is used. This instrument consists of 30 questions and the score can vary from 30 to 120.

The third psychological instrument relates to the Manchester DAQ. The DAQ is a questionnaire for the assessment of attitudes toward risk propensity while driving, constructed by Parker, Lajunen, and Stradling [26]. The questionnaire consists of 20 questions and the score can be in the interval from 20 to 100 points.

The fourth applied psychological instrument is the Questionnaire for Self-assessment of Driving Ability. Tronsmoen [27] devised this questionnaire. It consists of a set of statements about how drivers react in certain traffic situations. Based on the responses, it is possible to obtain information about participants' self-perception as a driver. There are 22 questions and the scores from this instrument can range from 22 to 88 points.

The output variable relates to the number of RTAs experienced by subjects. In this sample, participants reported the number of RTAs from 0 to 8; therefore, this variable is accordingly defined in this range.

Before the interview, each of the 305 participants in this research was informed about the key elements of the questionnaires. Besides, they were asked to voluntarily and honestly participate in interviewing by explaining the anonymous nature of the interview and that the collected answers will be presented only at an aggregate level.

A convenience sampling technique (a non-probability technique), was implemented. This technique implies a sample that is an available source of data for researchers. In this survey, there was a condition for the participants that they should regularly, at least once a month, drive at the State Road 22 in Serbia, commonly known as Ibar Highway. This road section represents an IB-class road, connecting the capital – Belgrade with Western Serbia. The authors chose this road section because this is one of the roads with the highest number of RTAs in the country.

In the procedure of data collection, two examination strategies were implemented, one for the drivers of privately owned vehicles, and another for professional drivers. The participating professional drivers completed paper-based questionnaires, while drivers of privately owned vehicles completed web-based questionnaires. The online response rate was 65.6%. To collect data on professional drivers, 12 bus companies and trucking companies from Serbia were contacted. The authors of this paper had some sort of previous collaboration with these companies, which might be an

explanation for a very high response rate. Namely, all 100 contacted bus drivers, and 102 truck drivers filled in the questionnaires.

### C. Design of FIS for modeling driver behavior

The fuzzy logic was proposed by Zadeh [28] offering the following basic definition: A fuzzy set  $A$  in  $X$  is characterized by a Membership Function (MF)  $\mu(x)$  which associates with each point in  $X$  a real number in the interval  $[0, 1]$ , with the value of  $\mu(x)$  at  $x$  representing the “grade of membership” of  $x$  in  $A$ .

In the literature, there are several examples of applying fuzzy logic to test the psychophysical characteristics of drivers. The authors of [29] designed a FIS to determine driving styles in terms of vehicle-human interactions. The acceleration, velocity, and distance between the preceding and host car were considered as parameters that affect the driving style. The same parameters were used in [30], while in [31] sudden acceleration and sudden turns are considered. In [32] authors implemented fuzzy logic to model driving behavior. However, their conclusions about driving style were based on the vehicle speed and acceleration measurement.

The authors of [33] created a FIS to predict the drowsiness level of the driver based on physiological reactions such as eye closure, gaze vector, head motion. A fuzzy system to warn the driver of drowsiness based on the captured facial images of drivers was proposed in [34]. The authors of [35] and [36] applied the fuzzy sets to compute the distraction of the drivers and proposed a corresponding road safety system.

The fuzzy logic was used also to form an accident prediction model based on input parameters that relate to the road infrastructure, such as road width, pavement conditions, average hourly traffic volume, speed, the number of access points to the highway, and traffic signs conditions [37], [38]. Selvi [39] establishes a similar prediction model based on fuzzy logic through factors such as traffic volume, rain status, and the geometry of the roads. A systematic review of the mentioned studies that use fuzzy logic for testing driver behavior and accident prediction is given in Table I.

The main difference between the previously mentioned studies and this paper is in the type of indicators used for the assessment of driver behavior. In the mentioned studies, the applied indicators can be explicitly measured by certain technical devices. Conversely, we use subjective indicators such as the assessment of personality and attitudes related to driver behavior. For this aim, we apply four psychological instruments. Based on the achieved scores from these instruments, we design the input variables of the proposed FIS. A result of the FIS represents the quantification of driver propensity for RTAs.

The final aim is to propose a FIS that acts as similar as possible to the pattern formed by real data. Finding this kind of FIS represents an optimization procedure that is the main subject of this paper. Additionally, the aim is to examine how the starting FIS in the optimization procedure affects the goodness of the found solution at the end of FIS optimization.

TABLE I  
THE USE OF FUZZY LOGIC FOR TESTING DRIVER BEHAVIOR AND ACCIDENT PREDICTION IN THE RELEVANT LITERATURE

Author(s) and Reference	Year of publication	Used indicators
Boyras, Acar, and Kerr [33]	2008	Eye closure, gaze vector, head motion
Wu and Chen [34]	2008	Facial images
Selvi [39]	2009	Traffic volume, rain status, and the geometry of the roads
Saleh, Aljaafreh, and Albhour [29]	2013	Acceleration, velocity, and distance between the preceding and host car
Fazio, Santamaria, De Rango, Tropea, and Seriani [32]	2016	Vehicle speed and acceleration
Wahaballa, Diab, Gaber, and Othman [37]	2017	Road width, pavement conditions, average hourly traffic volume, speed, the number of access points to the highway, and traffic signs conditions
Gaber, Wahaballa, Othman, and Diab [38]	2017	Annual average volume per lane, road width, speed, number of minor access points, road surface condition, and the percentile of sign per km of road
Riaz, Khadim, Rauf, Ahmad, Jabbar, and Chaudhry [35]	2018	Distance, speed, and distraction calculated by facial angle, eye movement, position.
Ou, Ouali, Bedawi, and Karray [36]	2018	Head pose estimation and the distraction recognition
Čubranić-Dobrodolac, Švadlenka, Čičević, and Dobrodolac [7]	2020	Personality traits and attitudes
Yüksel and Atmaca [31]	2020	Sudden acceleration and sudden turn
Bennajeh and Ben Said [30]	2021	Acceleration, velocity, and distance between the preceding and host car
<i>Our study</i>	<i>2021</i>	<i>Personality traits and attitudes</i>

There are three different approaches to forming the initial FIS proposed and tested. Let us assume that each input variable  $j$  is defined by  $N_j$  MFs and  $N_j$  is an odd number starting from 3. Here we analyze only the triangular and trapezoidal MFs in describing variables and we apply different approaches just on input variables.

The first approach is based on the symmetrical principle, where MFs are distributed along the entire interval of possible solutions, from  $I_{min}^j$  to  $I_{max}^j$ , and the axis of symmetry is in the middle of this interval. This method implies the use of triangular MFs and a point with the maximum degree for the central MF (MF number  $\lfloor \frac{N_j}{2} \rfloor$ , where MF number  $l$  is at the beginning of variable interval) is based on the axis of symmetry. A point with the maximum degree for the MF number  $l$  of variable  $j$  is located at the minimum value of the variable interval ( $I_{min}^j$ ). On the other hand, a point with the maximum degree for the MF number  $N_j$  of variable  $j$  is located at the maximum value of the variable interval ( $I_{max}^j$ ). The positions of points with the maximum degree for all MFs can be expressed by Eq. (1):

$$P^j MF_l = I_{min}^j + \frac{I_{max}^j - I_{min}^j}{N_j - 1} (l - 1), \quad (1)$$

where  $P^j MF_i$  is the position of a point with the maximum degree for MF number  $i$ , for variable  $j$ .

The second method is based on the asymmetric principle taking the mean value from the empirical sample of considered variable  $j$  ( $\bar{X}_j$ ) as a point with the maximum degree for the central MF. Therefore, the positions of points with the maximum degree for all MFs can be determined by Eq. (2):

$$P^j MF_i = \begin{cases} I_{min}^j + \frac{\bar{X}_j - I_{min}^j}{\left\lfloor \frac{N_j}{2} \right\rfloor - 1} (i - 1), & \forall i = 1, 2, \dots, \left\lfloor \frac{N_j}{2} \right\rfloor \\ \bar{X}_j + \frac{I_{max}^j - \bar{X}_j}{\left\lfloor \frac{N_j}{2} \right\rfloor - 1} \left( i - \left\lfloor \frac{N_j}{2} \right\rfloor \right), & i = \left( \left\lfloor \frac{N_j}{2} \right\rfloor + 1 \right), \dots, N_j \end{cases} \quad (2)$$

The asymmetric principle is also applied in the third method where the mean and extreme values from the empirical sample are taken into account when defining the points with the maximum degrees for MFs number  $1$ ,  $\left\lfloor \frac{N_j}{2} \right\rfloor$  and  $N_j$ . Therefore, in this method, the positions of points with the maximum degree for all MFs can be determined by Eq. (3), where  $X_{min}^j$  is the minimum value from the sample for variable  $j$ , and  $X_{max}^j$  is the maximum value from the sample for variable  $j$ :

$$P^j MF_i = \begin{cases} [I_{min}^j, X_{min}^j], & i = 1, I_{min}^j < X_{min}^j \\ X_{min}^j + \frac{\bar{X}_j - X_{min}^j}{\left\lfloor \frac{N_j}{2} \right\rfloor - 1} (i - 1), & \forall i = 1, 2, \dots, \left\lfloor \frac{N_j}{2} \right\rfloor \\ \bar{X}_j + \frac{X_{max}^j - \bar{X}_j}{\left\lfloor \frac{N_j}{2} \right\rfloor - 1} \left( i - \left\lfloor \frac{N_j}{2} \right\rfloor \right), & \forall i = \left( \left\lfloor \frac{N_j}{2} \right\rfloor + 1 \right), \dots, N_j \\ [X_{max}^j, I_{max}^j], & i = N_j, X_{max}^j < I_{max}^j \end{cases} \quad (3)$$

After the variables of FIS are defined, the next step is to determine the fuzzy rules. In all three previously described methods, we use a well-known approach proposed by Wang and Mendel [40]. This method is widely used in the literature [7], [41]-[43]. There are also examples of the combination of the Wang-Mendel method and some of the optimization algorithms, as is the case in this paper. For example, Yanar and Akyürek [44] combined the Wang-Mendel method with the simulated annealing metaheuristic.

Finally, when all parameters of FIS are defined, its performance should be tested by the optimization algorithm which will be further explained in Section 2.3. In this process, we use the objective function expressed by Eq. (4):

$$\text{Minimize } CD = \sum_{z=1}^{PA} |y^z - FIS(z)| \quad (4)$$

where  $CD$  is the cumulative deviation between the empirical data and results of created FIS structures during the optimization procedure,  $PA$  is the number of participants in the sample,  $y^z$  is the number of RTAs that participant  $z$  experienced in the driving history and  $FIS(z)$  is the result of FIS for participant  $z$ . Therefore,  $CD$  is a measure that describes how well a FIS describes the empirical data.

#### D. Implementation of BCO based algorithm

There are various types of bio-inspired methods, which represent powerful optimization algorithms for solving the task of FIS optimization [45]. When it comes to the use of metaheuristic algorithms based on artificial bees, there are several cases in the literature where the authors performed the optimization of FIS by this approach. Some authors use the approach proposed by Karaboga [46] named Artificial Bee Colony (ABC) optimization. The examples are the following. In [47] the authors optimized the load frequency control in the microgrid system. A methodology based on ABC to define Takagi–Sugeno fuzzy systems with enhanced performance from data is proposed in [48]. Konar and Bagis [49] applied different population-based approaches for the fuzzy modeling of the nonlinear systems and fuzzy rules optimization. They compared the performance of ABC, Particle Swarm Optimization (PSO), and Differential Evolution Algorithm (DEA).

On the other hand, some authors used the BCO approach for the optimization of FIS. BCO metaheuristic was proposed by Lučić and Teodorović [50]. Caraveo, Valdez, and Castillo [51] applied the BCO to optimize the FIS used as a water tank controller, which aims at controlling the water level in a tank, as well as to control the trajectory of the unicycle mobile robot. The same benchmark control problems were solved by Amador-Angulo and Castillo [52] who used BCO and type-2 fuzzy logic for tuning fuzzy controllers. In [53] the authors proposed an improvement of BCO by dynamic adaptation of the algorithm's parameters. In [54] a comparison is made among Particle swarm optimization (PSO), BCO, and the Bat Algorithm (BA), while the authors of [55] compared the performance of BCO, Differential Evolution (DE), and Harmony Search (HS) algorithms in the optimization of fuzzy controllers. Nikolić, Šelmić, Macura, and Čalić [13] recently proposed the BCO based algorithm for fuzzy membership functions tuning in the case of solving the problem of freight train energy consumption estimation. Further, a fuzzy-based ABC algorithm is employed to solve the construction site layout problem by satisfying the multi-objective function [56]. Mijović, Kalić, and Kuljanin [57] applied two meta-heuristics for FIS fine-tuning, where the BCO approach outperformed the PSO algorithm in terms of achieved solutions. A systematic review of the studies that use metaheuristic algorithms based on artificial bees to optimize FIS performance is given in Table II.

There are two types of BCO algorithm: constructive – the BCOc and improving – the BCOi. In the BCOc, there is no starting solution and it is generated gradually [10]. Conversely, the BCOi begins from a complete solution [9]. The BCOi type of algorithm to optimize the parameters of the fuzzy membership function is proposed for the first time in the paper [13]. Here, we use the BCOi type of algorithm as well; however, the main innovation of our algorithm is a newly devised strategy for the selection of points to be tested. Namely, in [13], the artificial bees choose the point that characterizes MFs to be modified at a certain step randomly. Conversely, in the algorithm proposed in this paper, we use a determined schedule of changing the points that define MFs during one iteration.

Considering one variable of FIS, in the proposed algorithm we start by changing MFs that are defined at the lowest values at the x-axis, and we continue to the highest values. The consequence of the proposed schedule is a more efficient manner of setting the constraints concerning the domains, i.e. possible values that the examined point can take. In the following text, we will give a more detailed explanation.

TABLE II  
THE USE OF ALGORITHMS BASED ON ARTIFICIAL BEES TO OPTIMIZE FUZZY INFERENCE SYSTEM PERFORMANCE

Author(s) and Reference	Year of publication	Considered problem	Type of algorithm based on bees
Chaiyatham, Ngamroo, Pothiya, and Vachirasricirikul [47]	2009	Load frequency control	ABC
Habbi, Boudouaoui, Karaboga, and Ozturk [48]	2015	Box-Jenkins gas furnace problem, nonlinear dynamic plant and nonlinear static system, and nonlinear plant tracking control problem	ABC
Caraveo, Valdez, and Castillo [51]	2016	Water tank controller, and trajectory of the unicycle mobile robot	BCO
Konar and Bagis [49]	2016	Antenna modeling problem and Box-Jenkins gas furnace problem	ABC
Amador-Angulo, Mendoza, Castro, Rodríguez-Díaz, Melin, and Castillo [53]	2016	Trajectory of autonomous mobile robot	BCO
Olivas, Amador-Angulo, Perez, Caraveo, Valdez, and Castillo [54]	2017	Trajectory of autonomous mobile robot	BCO
Amador-Angulo and Castillo [52]	2018	Water tank controller, and trajectory of the unicycle mobile robot	BCO
Castillo, Valdez, Soria, Amador-Angulo, Ochoa, and Peraza [55]	2019	Water tank, and the inverted pendulum	BCO
Nikolić, Selmić, Macura, and Kalić [13]	2020	Train energy consumption estimation	BCO
Nguyen [56]	2021	Construction site layout planning	ABC
Mijović, Kalić, and Kuljanin [57]	2021	Determining the airline market share	BCO
<i>Our study</i>	2021	<i>Modeling driver behavior</i>	<i>BCO</i>

A common feature of the previous research in the field is that an initial FIS in the optimization procedure was designed by an intuitive approach. One of the aims of this paper is exactly to demonstrate that the initial solution can affect the performance of an optimization procedure considering the goodness of the found solution. This is proven by comparing the values of

objective function after a certain number of iterations.

The general principles of the BCO metaheuristic and its comprehensive description can be found in [58]. The main characteristic of BCO is that the artificial bees collectively search for the best solution and each bee is independent in the searching procedure. However, in certain moments, they compare their obtained solutions and a bee decides to continue its search following some other bee or be loyal to its solution. The main idea behind this is that certain bees should follow the bees with better solutions in order to find the best possible solution. When a bee searches for a solution, this part of the algorithm is called forward pass, while flying back to the hive and comparison of achieved solutions is called backward pass. All decisions are made with an adequate probability level, having in mind the goodness of current achieved solutions. The purpose of introducing a probability in the bees' decision-making is to prevent being trapped in local optimums.

Each BCO algorithm is characterized by the following attributes [58]:

B – the number of bees involved in the search procedure,

IT – the number of iterations,

NP – the number of forward and backward passes in one iteration,

NC – the number of solution changes in one forward pass,

S – the best-known solution.

When it comes to the implementation of the BCO algorithm for FIS optimization, we introduce the following concept explained through five steps.

#### *Step 1: Definition of parameters - MF points to be changed*

Let us assume that the vertices of a triangular MF are marked with A, B, C, where their positions are defined by values of  $x$  and  $\mu(x)$ . The vertices A, B, C are distributed along  $x_i$  axis by ascending order, which means that the value  $x$  for the vertex A is the smallest, for B - middle, and for C - the highest. In the BCO algorithm, each vertex of MF is considered as a parameter  $P_f(ch)$  ( $f = 1, NP; ch = 1, NC$ ) to be changed  $NC$  times in one forward pass. In the proposed BCO algorithm, for each approach for the design of MFs and each considered variable, for the MF *number 1* we change just the parameter of MF that is characterized by the highest value of  $x$ . Conversely, for the MF *number  $N_j$*  we make changes just for the parameter of MF that is characterized by the smallest value of  $x$ . For all other MFs of a variable, we change all three parameters of MF. Therefore, if a variable is described by five MFs, this variable would be described by 11 parameters.

#### *Step 2: Setting the procedure of fuzzy rules generation from numerical data*

After each change of a parameter, the fuzzy rules should be set to form a complete FIS. This is done using the method proposed by Wang and Mendel [40]. When a FIS is completely designed, the effects of each change should be tested on the empirical data by applying Eq. (4).

#### *Step 3: Changing the values of parameters –forward pass*

The concept of the BCO algorithm is graphically shown in Fig. 2. In this case, it is assumed that  $NC=2$  which means that

in a forward pass there will be two changes of the parameter. In the proposed BCO algorithm, each parameter  $P_f(ch)$  is changed by the new value  $P'_f(ch)$  according to Eq. (5) and after each change and generation of new fuzzy rules, the performance of newly created FIS is evaluated by Eq (4).

$$P'_f(ch) = P_{fmin} + (P_{fmax} - P_{fmin}) * rand_{f,ch} \quad (5)$$

$P_{fmin}$  is the minimal value of the parameter  $P_f$ ,  $P_{fmax}$  is the maximum value of the parameter  $P_f$  ( $f = 1, NP$ ), and  $rand_{f,ch}$  is a random number in the interval from 0 to 1 which changes its value  $NP \times NC$  times in each iteration ( $ch = 1, NC$ ).

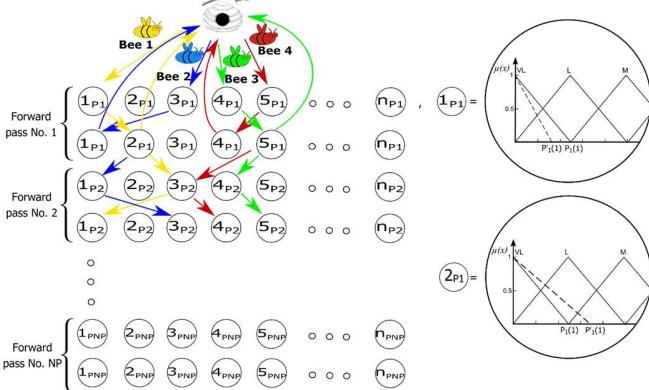


Fig. 2. The concept of the BCO algorithm for case  $B=4, NC=2$ .

#### Step 4: New strategy for the constraints concerning the values of tested parameters

When it comes to the way of choosing which  $P_f(ch)$  to be changed in a forward pass, we come to the most important difference between the algorithms found in the literature and our one. As previously explained, unlike in the algorithm proposed in [13], where the artificial bees choose which point to modify during the iteration's steps in a random manner, we use a determined schedule of changing the points which define MFs. As a consequence, a more efficient approach to finding better solutions is achieved.

When testing a parameter  $P_f(ch)$ , the domain of possible values should be determined. For this purpose, to provide the overlapping of corresponding MFs and to maintain the required order of considered parameters at  $x_i$  axis, there are certain constraints set. Here, the constraints in the case of variable  $x_i$  with five MFs (VLA, LA, MA, HA, and VHA) will be illustrated (Fig. 3). The same principle of forming constraints is valid for other variables of FIS.

To apply Eq. (5), we need to define the range where  $P'_f(ch)$  can take the values. Therefore, it is necessary to determine  $P_{fmin}$  and  $P_{fmax}$ . The notation used in the constraints is specified in Fig. 3. The symbol  $R$  is used for the parameter of MF that is the "right" bound of the MF which name is in the index of symbol  $R$ , and  $L$  for the parameter that is "left" bound of considered MF. The positions at the  $x$ -axis where MF has the maximum degree ( $\mu(x)=1$ ) is marked with  $M_{MF}$ , for example  $M_{VLA}$  for MF named VLA. In the considered case, the parameters:

$R_{VLA_{min}}, L_{LA_{min}}, M_{LA_{min}}, R_{LA_{min}}, L_{MA_{min}}, M_{MA_{min}}, R_{MA_{min}}, L_{HA_{min}}, M_{HA_{min}}, R_{HA_{min}}, L_{VHA_{min}}$  denotes  $P_{fmin}$ , while

$R_{VLA_{max}}, L_{LA_{max}}, M_{LA_{max}}, R_{LA_{max}}, L_{MA_{max}}, M_{MA_{max}}, R_{MA_{max}}, L_{HA_{max}}, M_{HA_{max}}, R_{HA_{max}}, L_{VHA_{max}}$  represents  $P_{fmax}$ .

In addition, the factor that emerges in the constraints is  $ODC$ , representing an overlapping and distance constant. The algorithm proposed in [13] enables the FIS structures with minimal overlapping of MFs, or these with the uncovered variable's domain by MFs (Part a of Fig. 4), as well as the FIS structures with illogical membership functions (Part b of Fig. 4). These authors calculate the output of unwanted FIS structures, but it is rejected later in the objective function by adding a penalty. Because it can be considered inefficient to perform the calculations that would later be abandoned without comparison with other solutions, we devised a new method for the selection of points to be tested during one iteration and set the  $ODC$  to design the appropriate FIS structures from the beginning of the algorithm, by this excluding a penalty constant that disturbs clear calculation of the objective function.

$$ODC = \frac{RB - LB}{n_{MF}} * 10\% \quad (6)$$

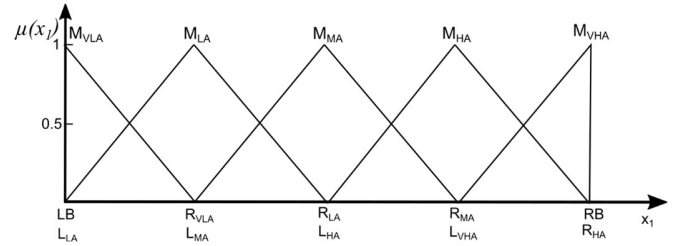


Fig. 3. The notation used in the constraints

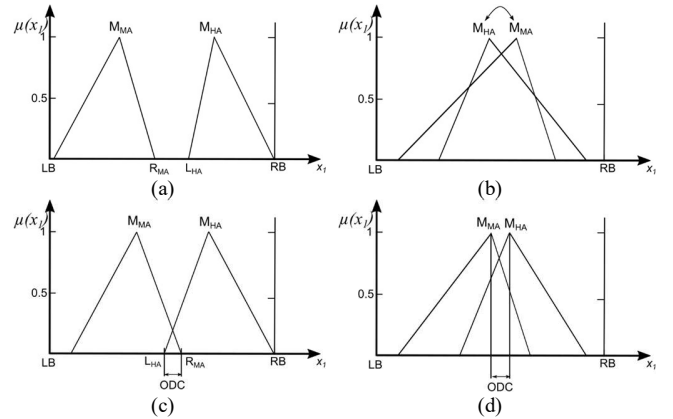


Fig. 4. Illustration of different constraints concerning  $P_f(ch)$  domains: (a) uncovered domain of the variable – Figure adjusted from [13]; (b) illogical membership functions – Figure adjusted from [13]; (c) the minimum allowed overlapping in the proposed algorithm –  $ODC$  value; (d) the minimum allowed distance between two membership functions for the points with the maximum degree ( $\mu(x)=1$ ) in the proposed algorithm –  $ODC$  value

In part (c) of Fig. 4,  $ODC$  denotes the minimum allowed overlapping, while the same value of  $ODC$  can be used as the minimum allowed distance between two membership functions for the points with the maximum degree ( $\mu(x)=1$ ), as shown in



part (d) of Fig. 4. The value of  $ODC$  should be calculated for each variable of FIS, by the Eq. (6), where  $LB$  is the lower bound of the domain of the variable,  $RB$  is the upper bound of the domain of the variable, and  $n_{MF}$  is the number of MFs that exist in the variable. To calculate the  $ODC$ , we introduce Eq. (6).

To calculate  $R_{VLA}$ ,  $L_{LA}$ ,  $M_{LA}$ ,  $R_{LA}$ ,  $L_{MA}$ ,  $M_{MA}$ ,  $R_{MA}$ ,  $L_{HA}$ ,  $M_{HA}$ ,  $R_{HA}$ ,  $L_{VHA}$  when considering the input variable  $x_i$ , the constraints are defined as follows:

$$\begin{aligned}
\text{For VLA: } & R_{VLA\_min} = M_{VLA} + ODC; \\
& R_{VLA\_max} = (M_{LA} + M_{MA})/2. \\
\text{For LA: } & L_{LA\_min} = LB; \\
& L_{LA\_max1} = R_{VLA} - ODC; L_{LA\_max2} = M_{LA} - ODC; \\
& L_{LA\_max} = \min(L_{LA\_max1}, L_{LA\_max2}). \\
& M_{LA\_min1} = LB + 2 * ODC; M_{LA\_min2} = L_{LA} + ODC; \\
& M_{LA\_min} = \max(M_{LA\_min1}, M_{LA\_min2}); \\
& M_{LA\_max1} = M_{MA} - 2 * ODC; M_{LA\_max2} = R_{LA} - ODC; \\
& M_{LA\_max} = \min(M_{LA\_max1}, M_{LA\_max2}). \\
& R_{LA\_min1} = M_{LA} + ODC; R_{LA\_min2} = L_{MA} + ODC; \\
& R_{LA\_min} = \max(R_{LA\_min1}, R_{LA\_min2}); \\
& R_{LA\_max} = (M_{MA} + M_{HA})/2. \\
\text{For MA: } & L_{MA\_min} = (M_{VLA} + M_{LA})/2; \\
& L_{MA\_max1} = R_{LA} - ODC; L_{MA\_max2} = M_{MA} - ODC; \\
& L_{MA\_max} = \min(L_{MA\_max1}, L_{MA\_max2}). \\
& M_{MA\_min1} = M_{LA} + 2 * ODC; M_{MA\_min2} = L_{MA} + ODC; \\
& M_{MA\_min} = \max(M_{MA\_min1}, M_{MA\_min2}); \\
& M_{MA\_max1} = M_{HA} - 2 * ODC; M_{MA\_max2} = R_{MA} - ODC; \\
& M_{MA\_max} = \min(M_{MA\_max1}, M_{MA\_max2}). \\
& R_{MA\_min1} = M_{MA} + ODC; R_{MA\_min2} = L_{HA} + ODC; \\
& R_{MA\_min} = \max(R_{MA\_min1}, R_{MA\_min2}); \\
& R_{MA\_max} = (M_{HA} + RB)/2. \\
\text{For HA: } & L_{HA\_min} = (M_{LA} + M_{MA})/2; \\
& L_{HA\_max1} = R_{MA} - ODC; L_{HA\_max2} = M_{HA} - ODC; \\
& L_{HA\_max} = \min(L_{HA\_max1}, L_{HA\_max2}). \\
& M_{HA\_min1} = M_{MA} + 2 * ODC; M_{HA\_min2} = L_{HA} + ODC; \\
& M_{HA\_min} = \max(M_{HA\_min1}, M_{HA\_min2}); \\
& M_{HA\_max1} = RB - 2 * ODC; M_{HA\_max2} = R_{HA} - ODC; \\
& M_{HA\_max} = \min(M_{HA\_max1}, M_{HA\_max2}). \\
& R_{HA\_min1} = M_{HA} + ODC; R_{HA\_min2} = L_{VHA} + ODC; \\
& R_{HA\_min} = \max(R_{HA\_min1}, R_{HA\_min2}); \\
& R_{HA\_max} = RB. \\
\text{For VHA: } & L_{VHA\_min} = (M_{MA} + M_{HA})/2; \\
& L_{VHA\_max1} = R_{HA} - ODC; L_{VHA\_max2} = RB - ODC; \\
& L_{VHA\_max} = \min(L_{VHA\_max1}, L_{VHA\_max2}).
\end{aligned}$$

The concrete values in the set constraints are dynamically changing during the execution of the algorithm. This implies that each formed FIS in the testing procedure has its own constraints. This kind of dynamically changing constraints is possible only in the case of a determined schedule of changing the points  $P_f(ch)$ .

#### Step 5: Comparison of achieved solutions – backward pass

In Fig. 2, the first row represents a set of possible values that the first parameter can take. Although this is an extremely large range of possible values, it is a finite number denoted by the letter  $n$ . In Fig. 2,  $n$  has a different notation in each forward pass to demonstrate that different parameters can take other  $n$  possible values at different variable domains across  $x_i$  axis. Therefore, a set of possible values that considered parameters

can take is referenced as  $n_{pf}$ , where  $P$  in the index indicates that it is a possible value of a parameter and  $f$  gives the information about which of  $NP$  parameters is changing ( $f = 1, NP$ ).

In the first forward pass denoted by No.1, each bee takes one of  $n_{p1}$  values for the first parameter  $P_1(1)$ . Based on the selected value, a bee generates the new FIS and the value of its objective function is calculated. Then each bee takes some other of  $n_{p1}$  values for the same first parameter  $P_1(2)$  and the new values of objective functions are calculated. Since the  $NC = 2$ , after two changes a bee should decide which of two values will take and bring to the hive for comparison with other bees. A decision about which change a bee should take is made by a certain probability level. For this purpose, we introduce the probability of choosing one of two values in this case ( $PR_f$ ) which is calculated based on a well-known *Logit* model. Having in mind that the objective function relates to minimization, the calculation of  $PR_f$  is done as shown in Eq. (7) [59].

$$PR_f = \frac{e^{(1-CD_f)}}{\sum_{f=1}^{NC} e^{(1-CD_f)}} \quad (7)$$

$CD_f$  is the value of the objective function for change number  $f$ . To make a selection decision, a number from the interval (0,1) is randomly generated. Based on the calculated probability value  $PR_f$  and the value of a randomly generated number, a bee decides which value of the parameter will adopt in the considered forward pass.

A concept of bees' solutions comparison is also based on probability. First, a bee should decide to be loyal or not to its obtained solution. This procedure can be done as explained in [8]. The quality of the solutions generated by bees is normalized as shown in Eq (8):

$$N_b = \frac{CD_{bmax} - CD_b}{CD_{bmax} - CD_{bmin}} \quad (8)$$

where  $N_b$  is a normalized value of objective function obtained by  $b$ -th bee,  $CD_{bmax}$  is the highest value of objective function found by all bees,  $CD_b$  is the value of objective function found by  $b$ -th bee and  $CD_{bmin}$  is the lowest value of objective function found by all bees.

A bee decides whether to remain loyal to its solution based on probability ( $PRL_b$ ) calculated as presented in Eq. (9):

$$PRL_b = e^{-(N_{bmax} - N_b)} \quad (9)$$

where  $N_{bmax}$  is the maximum normalized value of the objective function considering all bees.

If the bee decides not to be loyal to its solution, it chooses which bee to follow. A probability that the bee that is not loyal will follow the  $b$ -th bee ( $PRF_b$ ) is expressed by Eq. (10) where  $L$  is a set of loyal bees.

$$PRF_b = \frac{N_b}{\sum_{l \in L} N_l} \quad (10)$$

In the illustrated case in Fig. 2, Bees 1 and 3 remained loyal

to their previous solutions, while Bees 2 and 4 abandoned their solutions and decided to continue their search following the solutions of Bee 1 and 3, respectively.

A general procedure of the BCO algorithm implemented for FIS performance optimization is presented in Table III. In the proposed pseudocode, the used symbols are as previously defined (inputs:  $B$ ,  $IT$ ,  $NP$ ,  $NC$ ; output:  $S$ ). A case when the proposed algorithm is performed ones, including  $IT$  iterations, will be called an experiment ( $E$ ). It is welcome to repeat the experiment more times and to compare the results. In this paper, we defined the value of  $IT$  to be 20 and repeated the experiment 10 times for each of the three different approaches ( $m$ ) for defining MFs. To compare the proposed approaches, we calculated the mean values of 10 experiments.

TABLE III

PSEUDOCODE OF IMPLEMENTED BCO ALGORITHM FOR FIS OPTIMIZATION

1. for  $m = 1$  to 3
2. Choose one of the three proposed approaches for the design of MF.
3. for  $e = 1$  to  $E$
4. for  $t = 1$  to  $IT$
5. for  $b = 1$  to  $B$
6. Assign an initial solution to the bee  $b$  based on the chosen approach in Step 2.
7. for  $f = 1$  to  $NP$
8. for  $b = 1$  to  $B$
9. for  $ch = 1$  to  $NC$
10. Evaluate the performed changes in the solution of the bee  $b$ .  
Chose one change considering the obtained values of the objective function.
11. for  $b = 1$  to  $B$
12. Based on the values of the objective function for each bee, decide whether the bee  $b$  is loyal to its solution. If the bee  $b$  is not loyal, chose the bee to be followed by the bee  $b$ .
13. Evaluate all solutions and find the best one  $S$ .
14. Output the best solution for each iteration
15. Output the best solution for each experiment.

### III. CALCULATIONS AND SIMULATION RESULTS

The considered sample in this study included 305 drivers, comprising 103 drivers of privately owned vehicles, 100 bus drivers, and 102 truck drivers. The ratio between male and female respondents was 88/12 %. This relationship was expected due to the demanding nature of professional driving and the fact that generally, a large majority of drivers are male.

The domains and descriptive statistics for the scores achieved by respondents are shown in Table IV. The following symbols are introduced: variable  $x_1$  is the score from the ADBQ,  $x_2$  from the BIS-11,  $x_3$  from the DAQ,  $x_4$  from the Questionnaire for Self-Assessment of Driving Ability and  $y$  is the number of traffic accidents experienced by participants.

As explained in Section 2, we test three approaches for defining variables. In all approaches, the input variables are described by five MFs. For all input variables, the MFs are described as follows: *very low*, *low*, *medium*, *high*, and *very high* level of the considered variable. For example, the score from the ADBQ gives the information about driver *aggressiveness*; accordingly, five fuzzy sets that describe this input variable are the following: *very low aggressiveness* (VLA), *low aggressiveness* (LA), *medium aggressiveness* (MA), *high aggressiveness* (HA) and *very high aggressiveness* (VHA). The same principle is implemented when the MFs of

other variables are named. The BIS-11 test is named *impulsiveness* and the letter "I" is used at the end of the name of MFs, the DAQ is considered as *risk* and the letter "R" is taken, while the Questionnaire for Self-Assessment of Driving Ability is abbreviated as *self-assessment*, hence the letter "S" is used.

TABLE IV

DOMAIN INTERVALS FOR  $X_1, X_2, X_3, X_4$  AND  $Y$  AND DESCRIPTIVE STATISTICS OF THE SAMPLE

Variable	Domain	Descriptive statistics of the sample		
		Minimum	Mean	Maximum
$x_1$	[20,120]	26	49.46	76
$x_2$	[30,120]	49	68.44	86
$x_3$	[20,100]	24	62.52	83
$x_4$	[22,88]	34	66.58	88
$y$	[0,8]	0	1.33	8

Using the first approach, where the input variables are defined based on the symmetry principle, the MFs are distributed as shown in Fig. 5. As can be seen, the axis of symmetry is positioned in the middle of the variable domain. In the case of *aggressiveness*, this axis is at point 70, for *impulsiveness* – at point 75, for *risk* – at point 60, and for *self-assessment* – at point 55. To offer more precise information about the position of MFs, the concrete values for which the degree of corresponding MF is equal to 1 are presented in Table V.

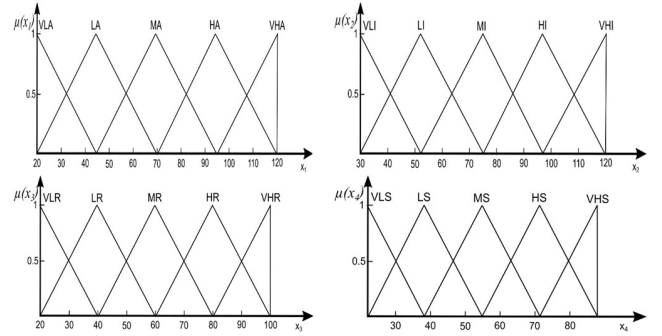


Fig. 5. MFs for input variables defined by the symmetric principle

TABLE V

THE VALUES OF VARIABLES  $x_i$  ( $i=1:4$ ) FOR WHICH THE DEGREE OF CORRESPONDING MF IS EQUAL TO 1 ( $\mu(x_i) = 1$ )

Variable	Type of fuzzy set				
	Very low	Low	Medium	High	Very high
<i>Symmetric approach</i>					
$x_1$	20	45	70	95	120
$x_2$	30	52.5	75	97.5	120
$x_3$	20	40	60	80	100
$x_4$	22	38.5	55	71.5	88
<i>The asymmetric approach based on the mean value</i>					
$x_1$	20	34.73	49.46	84.73	120
$x_2$	30	49.22	68.44	94.22	120
$x_3$	20	41.26	62.52	81.26	100
$x_4$	22	44.29	66.58	77.29	88
<i>The asymmetric approach based on mean and extreme values</i>					
$x_1$	[20,26]	37.73	49.46	62.73	[76,120]
$x_2$	[30,49]	58.72	68.44	77.22	[86,120]
$x_3$	[20,24]	43.26	62.52	72.76	[83,100]
$x_4$	[22,34]	50.29	66.58	77.29	88

The second approach is based on the asymmetric principle, taking the mean value from the sample as the point for which

the central MF has the maximum degree (equal to 1). As can be seen from Table 5, the value 49.46 is the value of variable  $x_1$  for which  $\mu(x_1) = 1$  for the MF *Medium* (MA). The limit values of a variable  $x_1$  are taken as  $\mu(x_1) = 1$  for the MF *Very low* (20) and *Very high* (120). The space between the mean and limit values is symmetrically divided, where the position of the axis of symmetry is a point where  $\mu(x_1) = 1$  for the fuzzy sets *Low* (34.73) and *High* (84.73). The same principle is implemented for the remaining three input variables and the input variables are designed by the second approach as shown in Fig. 6.

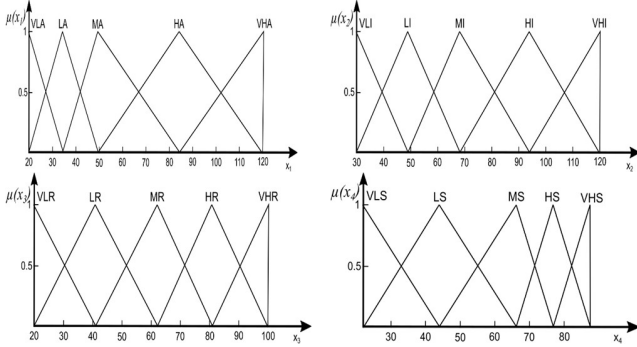


Fig. 6. MFs for input variables defined by the asymmetric principle based on the mean value

The third approach is based on the asymmetric principle, where the characteristic points are the mean and extreme values from the data sample. For example, the possible values of the variable *aggressiveness* are from 20 to 120. Considering the values from the sample of 305 drivers, the minimum value was 26 and the maximum 76. Based on the proposed approach, the scores below 26 belong to the fuzzy set *very low aggressiveness* (VLA) with the value of MF equal to 1 ( $\mu(x_1) = 1$ ). On the other hand, scores above 76 are in the fuzzy set *very high aggressiveness* (VHA), also with the value of MF equal to 1. The value 49.46 was taken as the highest MF value ( $\mu(x_1) = 1$ ) in the fuzzy set *medium aggressiveness* (MA), the same as in the second method. The remaining two MFs, LA and HA were defined between the extreme values from the sample and mean, as shown in Fig. 7. Other input variables are defined in the same manner.

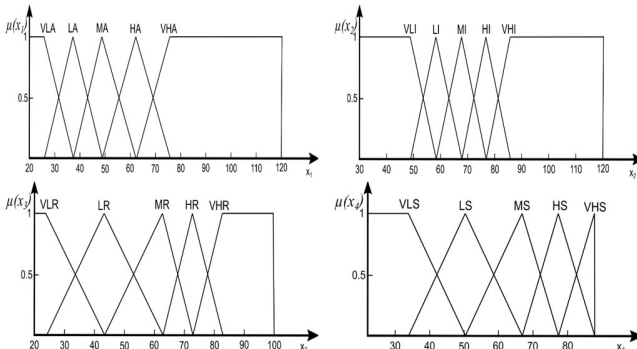


Fig. 7. MFs for input variables defined by the asymmetric principle based on mean and extreme values

To describe the output variable, seven MFs were introduced unlike the cases for input variables where five MFs were used. The domain of the output variable covers just 9 points;

however, the number of MFs is increased in this case because the RTAs are relatively rare events and the intention was to describe each category of drivers as precise as possible. The following MF were introduced: *very small number of accidents* (VSNA), *small number of accidents* (SNA), *moderately small number of accidents* (MSNA), *medium number of accidents* (MNA), *moderately high number of accidents* (MHNA), *high number of accidents* (HNA), and *very high number of accidents* (VHNA). The variable  $y$  was defined as shown in Fig. 8.

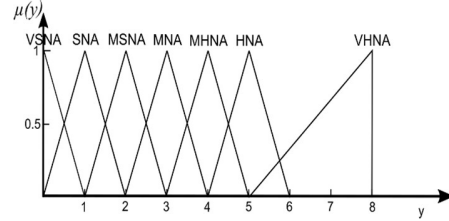


Fig. 8. MFs for the output variable

Testing of the proposed approaches for defining variables in the FIS is done by the optimization procedure using the proposed BCO algorithm. Each input variable is described by five MFs. For MF *number 1* just the parameter of this MF that is of the highest value at  $x_i$  axis is tested, while for MF *number 5* just the parameter of the lowest value at  $x_i$  axis is considered. In the case of MFs *numbers 2, 3, and 4*, all three parameters of each triangular MF are tested. In total, there are 11 parameters analyzed for each variable. Since there are four input variables, each of them described by five MFs, the total number of parameters ( $P$ ) to be examined is 44. As previously explained in Section 2, testing a parameter represents a forward pass, therefore  $NP=44$ . When testing a parameter, the domain of possible values should be determined. For this purpose, to provide the overlapping of corresponding MFs and to maintain the required order of considered parameters at  $x_i$  axis, there are 88 constraints set. Other parameters of the implemented BCO algorithm are the following:  $B=4$ ,  $NC=5$ ,  $IT=20$ .

The simulation procedure implied 10 experiments for each considered approach for defining variables. For each iteration, the mean values of 10 experiments is presented in Fig. 9. Having in mind that there are 4 bees, 5 changes made by each bee in a forward pass, 44 forward passes, 20 iterations, 10 experiments, 3 approaches and that each FIS is tested on the sample of 305 drivers, the results present in Fig. 9 are based on 161,040,000 evaluated fuzzy inference systems. The total execution time is around 90 hours, i.e. almost 4 days. Although this can be considered as a long computation time, in our case, it is acceptable since the proposed algorithm is not intended to be used for the management of some processes in real-time. Just the final obtained FIS that provides the best performance should be used in practice. However, it is interesting to compare the performance of different BCO algorithms. By analyzing Table VI, it can be concluded that the computation time is affected to the largest extent by the number of variables that exist in a FIS, as well as by the number of MFs per variable. By increasing these two parameters, the fuzzy rules database exponentially increases which also prolongs the calculation, particularly if a certain additional algorithm is introduced for new fuzzy rules

generation after each change. Boosting the complexity of the algorithm provides better solutions and, as previously explained, this is justified in our case.

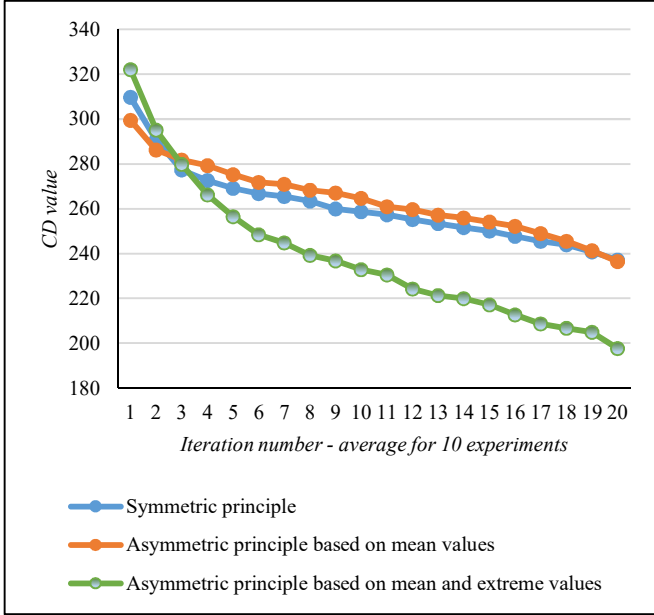


Fig. 9. A comparison between three approaches for defining variables of FIS based on average CD values in 10 experiments with 20 iterations

TABLE VI  
THE PARAMETERS OF THE BCO ALGORITHM THAT AFFECT THE EXECUTION TIME

Authors and Reference	Nikolić Šelmić, Macura, Čalić [13]	Mijović, Kalić, Kuljanin [57]	Our study
Number of input variables	3	2	4
Number of MFs in each input variable	3	NA	5
Number of output variables	1	1	1
Number of MFs in output variable	5	7	7
Sample	15	98	305
The certain algorithm applied for new fuzzy rules generation after each change	No	No	Yes
Number of passes in each iteration	3	3	44
Number of bees	15	40	4
Execution time for one iteration [min]	Significantly less than 1	Significantly less than 1	Around 9

The results of the best-found FIS structures after each experiment are presented in Table VII. To determine whether there is a statistically significant difference between the three approaches for setting an initial solution concerning the achieved results in the optimization procedure, we conducted a paired t-test. The conclusion is that there is no difference between the Symmetric approach and the Asymmetric approach based on the mean value ( $p=0.524$ ), while the Asymmetric approach based on mean and extreme values differs from both other approaches ( $p<0.001$  in both cases).

Finally, the task is to find a FIS with a minimum value of the objective function. This would be the best found FIS that can be used as a decision-making tool for various purposes in the transportation field. The best found FIS is created by the asymmetric approach based on mean and extreme values and its CD value is equal to 190.6803. The MFs of input variables of this FIS are presented in Fig. 10.

TABLE VII  
THE MINIMAL VALUES OF CD IN 10 EXPERIMENTS FOR EACH CONSIDERED APPROACH

Experiment Number	Symmetric approach (CD)	The asymmetric approach based on the mean value (CD)	The asymmetric approach based on mean and extreme values (CD)
1	243.9240	247.5702	207.5843
2	241.1064	245.7423	203.4848
3	240.9741	242.2948	202.8990
4	239.1694	241.0987	202.0099
5	238.6924	240.2350	198.9663
6	237.9139	233.1188	194.0601
7	237.0992	232.9170	193.4670
8	234.9182	230.5881	192.3154
9	230.4864	227.3439	191.4037
10	227.4326	222.9927	190.6803

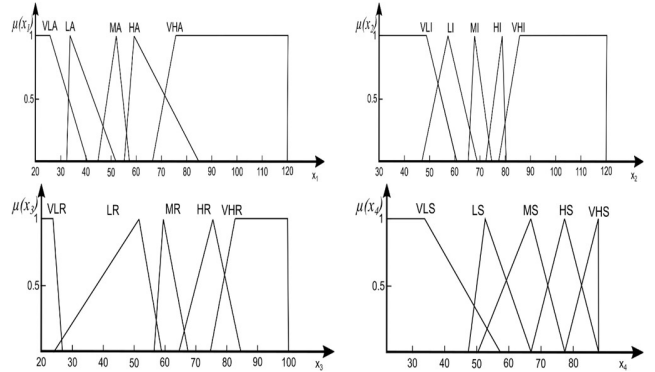


Fig. 10. MFs for input variables of the best found FIS

#### IV. CONCLUSION

This paper aimed to perform the optimization of FIS that can be used as a decision-making tool when assessing a driver propensity for RTAs based on the psychological traits and to examine the effects of initial FIS structures in the optimization procedure. There are three proposed approaches: Symmetric approach, Asymmetric approach based on the mean value, and Asymmetric approach based on mean and extreme values. The BCO algorithm proposed in this paper confirmed that the third method gives the best results. This conclusion may be useful twofold. First, having in mind that the third method for defining variables is the most suitable, the initial FIS in the optimization procedure can be easier and more effectively defined. Second, in the case when there is a task just to form a FIS for some purpose and there is a lack of time for the optimization procedure, by using the third method, the designed FIS will more probably offer better solutions than created randomly or by using other two tested methods.

Besides a contribution to the methodological field, this

paper proposed a FIS that can be used for different purposes in transportation. The best found FIS can be considered as a decision-making tool in recruitment procedures for professional drivers to assess a driver propensity for RTAs. Based on information obtained by implementing the proposed FIS, the training and education processes for candidates applying for a driving license may be improved. A particular significant application can be in the programs for the prevention of accidents and violations of laws, or the rehabilitation of drivers according to their personality traits in the cases when they have been convicted for traffic offenses. Having in mind the growing consequences of RTAs, both measured in the lost lives and as financial costs, the significance of the proposed model is evident. Transport demands are on the rise, especially in the cities, where RTAs, besides already described negative effects, can generate severe traffic congestions. Therefore, the proposed decision-making tool offers various benefits, from saving the lives of people to significant economic, environmental, and social benefits.

When it comes to the limitations of this research, it should be kept in mind that the results are based on the data collected by the drivers' self-reports. Such methods of data collection can lead to distortions due to socially desirable answers. Although respondents were familiar with the anonymous nature of testing as well as guaranteed confidentiality of the collected data, it is assumed that they still had some kind of restraint in responding concerning certain aspects of behavior. Further research directions should be focused on the minimization or elimination of these limitations. However, despite the mentioned limitations, the results of this study indicate an important role of certain personality traits in risky behavior on the roads.

In addition, the recommendation for future research can be to broaden the optimization algorithm to the different shapes of MFs or another number of MFs. Additionally, since the fuzzy rules base is formed in this paper based on the Wang-Mendel method, testing some other approaches would be welcome. Speaking about the sample, this study provides information on driver behavior in Serbia; however, as a possible future research direction, it would be of interest to carry out the same investigation in different countries.

#### ACKNOWLEDGMENT

The authors are grateful for the valuable comments of the Editor-in-Chief, the Department Editor Dilek Cetindamar, and the two anonymous reviewers, who helped to improve the manuscript greatly.

#### REFERENCES

- [1] National Highway Traffic Safety Administration, Washington, USA. (2020). *Fatality Analysis Reporting System*. [Online]. Available: <https://www-fars.nhtsa.dot.gov/Main/index.aspx>
- [2] European Commission, Brussels, Belgium. (2019). *Annual Accident Report 2018*, [Online]. Available: [https://ec.europa.eu/transport/road\\_safety/sites/roadsafety/files/pdf/statistics/dacota/asr2018.pdf](https://ec.europa.eu/transport/road_safety/sites/roadsafety/files/pdf/statistics/dacota/asr2018.pdf)
- [3] B. De Brabander and L. Vereeck, "Valuing the Prevention of Road Accidents in Belgium," *Transport Rev*, vol. 27, no. 6, pp. 715-732, Oct. 2007, 10.1080/01441640701275362.
- [4] A. García-Altés and K. Pérez, "The economic cost of road traffic crashes in an urban setting," *Inj Prev*, vol. 13, no. 1, pp. 65-68, Feb. 2007, 10.1136/ip.2006.012732.
- [5] E. Kuşkan, M. Yasin Çodur, and A. Atalay, "Speed violation analysis of heavy vehicles on highways using spatial analysis and machine learning algorithms," *Accident Anal Prev*, vol. 155, no. 106098, Jun. 2021, 10.1016/j.aap.2021.106098.
- [6] S. Newnam and B. Watson, "Work-related driving safety in light vehicle fleets: A review of past research and the development of an intervention framework," *Safety Sci*, vol. 49, no. 3, pp. 369-381, Mar. 2011, 10.1016/j.ssci.2010.09.018.
- [7] M. Čubranić-Dobrodolac, L. Švadlenka, S. Čičević, and M. Dobrodolac, "Modelling driver propensity for traffic accidents: a comparison of multiple regression analysis and fuzzy approach," *Int J Inj Control Sa*, vol. 27, no. 2, pp. 156-167, 2020, 10.1080/17457300.2019.1690002.
- [8] M. Nikolić, "Disruption management in transportation by the bee colony optimization metaheuristic," Ph.D. Dissertation, University of Belgrade, Serbia, 2015.
- [9] G. Z. Marković, "Wavelength Converters Placement in Optical Networks Using Bee Colony Optimization," *Adv Electr Comput En*, vol. 16, no. 1, pp. 3-10, Feb. 2016, 10.4316/AECE.2016.01001.
- [10] G. Z. Marković, "Revenue-driven Lightpaths Provisioning over Optical WDM Networks Using Bee Colony Optimization," *Int J Comput Int Sys*, vol. 10, no. 1, pp. 481-494, Jan. 2017, 10.2991/ijcis.2017.10.1.33.
- [11] G. Z. Marković, "Routing and spectrum allocation in elastic optical networks using bee colony optimization," *Photonic Netw Commun*, vol. 34, no. 3, pp. 356-374, Jul. 2017, 10.1007/s11107-017-0706-z.
- [12] B. Dimitrijević, D. Teodorović, V. Simić, and M. Šelmić, "Bee colony optimization approach to solving the anticommuting location problem," *J Comput Civil Eng*, vol. 26, no. 6, pp. 759-768, Nov. 2012, 10.1061/(ASCE)CP.1943-5487.0000175.
- [13] M. Nikolić, M. Šelmić, D. Macura, and J. Čalić, "Bee Colony Optimization Metaheuristic for Fuzzy Membership Functions Tuning," *Expert Syst Appl*, vol. 158, no. 113601, Nov. 2020, 10.1016/j.eswa.2020.113601.
- [14] C. Wangdi, M. S. Gurung, T. Duba, E. Wilkinson, Z.M. Tun, and J.P. Tripathy, "Burden, pattern and causes of road traffic accidents in Bhutan, 2013-2014: a police record review," *Int J Inj Control Sa*, vol. 25, no. 1, pp. 65-69, 2018, 10.1080/17457300.2017.1341930.
- [15] D. Sam, C. Velanganni, and T. E. Evangelin, "A vehicle control system using a time synchronized Hybrid VANET to reduce road accidents caused by human error," *Veh Commun*, vol. 6, pp. 17-28, Oct. 2016, 10.1016/j.vehcom.2016.11.001.
- [16] F. Zhang, S. Mehrotra, and S. C. Roberts, "Driving distracted with friends: Effect of passengers and driver distraction on young drivers' behavior," *Accident Anal Prev*, vol. 132, no. 105246, Nov. 2019, 10.1016/j.aap.2019.07.022.
- [17] D. Pešić, B. Antić, E. Smailović, and N. Marković, "Driving under the influence of alcohol and the effects of alcohol prohibition-Case study in Serbia," *Traffic Inj Prev*, vol. 20, no. 5, pp. 467-471, Jun. 2019, 10.1080/15389588.2019.1612058.
- [18] M. Čubranić-Dobrodolac, S. Čičević, M. Dobrodolac, and M. Nešić, "The risks associated with using a mobile phone by young drivers," *Transport*, vol. 28, no. 4, pp. 381-388, Dec. 2013, 10.3846/16484142.2013.865672.
- [19] J. Elander, R. West, and D. French, "Behavioural Correlates: Individual Differences in Road-Traffic Crash Risk: An Examination of Methods and Findings," *Psychol Bull*, vol. 113, no. 2, pp. 279 - 294, 1993, 10.1037/0033-2909.113.2.279.
- [20] A. Furnham and J. Saipé, "Personality correlates of convicted drivers," *Pers Individ Differ*, vol. 14, no. 2, pp. 329-336, Feb. 1993, 10.1016/0191-8869(93)90131-L.
- [21] P. Sârbescu and L. Maricuțoiu, "Are you a 'bad driver' all the time? Insights from a weekly diary study on personality and dangerous driving behavior," *J Res Pers*, vol. 80, pp. 30-37, Jun. 2019, 10.1016/j.jrjp.2019.04.003.
- [22] Y. Zheng, Y. Ma, and J. Cheng, "Effects of personality traits and sociocognitive determinants on risky riding behaviors among Chinese e-bikers," *Traffic Inj Prev*, vol. 20, no. 8, pp. 838-843, Nov. 2019, 10.1080/15389588.2019.1655144.
- [23] M. Čubranić-Dobrodolac, K. Lipovac, S. Čičević, and B. Antić, "A model for traffic accidents prediction based on driver personality traits assessment," *Promet*, vol. 29, no. 6, pp. 631-642, Dec. 2017, 10.7307/ptt.v29i6.2495.

- [24] M. Mouloua, J. C. Brill, and E. Shirkey, "Gender Differences and Aggressive Driving Behavior: A Factor Analytic Study," *Hum Fac Erg Soc P*, vol. 51, no. 18, pp. 1283–1286, Oct. 2007, 10.1177/154193120705101850.
- [25] J. H. Patton, M. S. Stanford, and E. S. Barratt, "Factor structure of the Barratt Impulsiveness Scale," *J Clin Psychol*, vol. 51, no. 6, pp. 768–774, Nov. 1995, 10.1002/1097-4679(199511)51:6%3C768::AID-JCLP2270510607%3E3.0.CO;2-1.
- [26] D. Parker, T. Lajunen, and S. Stradling, "Attitudinal predictors of interpersonally aggressive violations on the road," *Transport Res F-Traf*, vol. 1, no. 1, pp. 11–24, Aug. 1998, 10.1016/S1369-8478(98)00002-3.
- [27] T. Tronsmoen, "Associations between self-assessment of driving ability and accident risk among young drivers," *Transport Res F-Traf*, vol. 11, no. 5, pp. 334–346, Sep. 2008, 10.1016/j.trf.2008.02.002.
- [28] L. A. Zadeh, "Fuzzy Sets," *Inform Control*, vol. 8, no. 3, pp. 338–353, Jun. 1965, 10.1016/S0019-9958(65)90241-X.
- [29] M. Saleh, A. Aljaafreh, and N. Albdour, "Fuzzy-based recognition model for driving styles," *Int J Electr Comput Eng Syst*, vol. 16, no. 1, pp. 816–819, Sep. 2013.
- [30] A. Bennajeh and L. Ben Said, "Driving control based on bilevel optimization and fuzzy logic," *Int J Intell Syst*, May 2021, 10.1002/int.22441.
- [31] A. S. Yuksel and S. Atmaca, "Driver's black box: a system for driver risk assessment using machine learning and fuzzy logic," *J Intell Transport S*, Dec. 2020, 10.1080/15472450.2020.1852083.
- [32] P. Fazio, A. F. Santamaria, F. De Rango, M. Tropea, and A. Serianni, "A new application for analyzing driving behaviour and environment characterization in transportation systems based on a fuzzy logic approach," *Proceedings of SPIE 9837, Unmanned Systems Technology XVIII*, 983707, Apr. 2016, 10.1117/12.2228432.
- [33] P. Boyraz, M. Acar, M., and D. Kerr, "Multi-sensor driver drowsiness monitoring," *P I Mech Eng D-J Aut*, vol. 222, no. 11, pp. 2041–2062, Nov. 2008, 10.1243/09544070JAUTO513.
- [34] J. D. Wu and T.-R. Chen, "Development of a drowsiness warning system based on the fuzzy logic images analysis," *Expert Syst Appl*, vol. 34, no. 2, pp. 1556–1561, Feb. 2008, 10.1016/j.eswa.2007.01.019.
- [35] F. Riaz, S. Khadim, R. Rauf, M. Ahmad, S. Jabbar, and J. Chaudhry, "A validated fuzzy logic inspired driver distraction evaluation system for road safety using artificial human driver emotion," *Comput Netw*, vol. 143, pp. 62–73, Oct. 2018, 10.1016/j.comnet.2018.06.007.
- [36] C. Ou, C. Ouali, S. M. Bedawi, and F. Karray, "Driver Behavior Monitoring Using Tools of Deep Learning and Fuzzy Inferencing," *2018 IEEE Int. Conf. Fuzzy Syst*, pp. 1–7, Jul. 2018, 10.1109/FUZZ-IEEE.2018.8491511.
- [37] A. M. Wahaballa, A. Diab, M. Gaber, and A. M. Othman, "Sensitivity of traffic accidents mitigation policies based on fuzzy modeling: A case study," *2019 IEEE Intell. Transp. Syst. Conf. ITSC 2019*, Oct. 2017, pp. 1–6, 10.1109/ITSC.2017.8317589.
- [38] M. Gaber, A. M. Wahaballa, A. M. Othman, and A. Diab, "Traffic accidents prediction model using fuzzy logic: Aswan Desert road case study," *J Eng Sci*, vol. 45, no. 1, pp. 28–44, Jan. 2017, [http://www.aun.edu.eg/journal\\_files/515\\_J\\_9273.pdf](http://www.aun.edu.eg/journal_files/515_J_9273.pdf)
- [39] Ö. Selvi, "Traffic accident predictions based on fuzzy logic approach for safer urban environments, case study: Izmir metropolitan area," Ph.D. dissertation, Izmir Institute of Technology, Turkey, 2009.
- [40] L. Wang and J. Mendel, "Generating fuzzy rules by learning from examples," *IEEE Trans Syst Man Cybern Syst*, vol. 22, no. 6, pp. 1414–1427, Nov.–Dec. 1992, 10.1109/21.199466.
- [41] P. C. Chang, J. C. Hieh, and T. W. Liao, "Evolving fuzzy rules for due-date assignment problem in semiconductor manufacturing factory," *J Intell Manuf*, vol. 16, no. 4–5, pp. 549–557, Oct. 2005, 10.1007/s10845-005-1663-4.
- [42] E. D'Andrea and B. Lazzerini, "A hierarchical approach to multi-class fuzzy classifiers," *Expert Syst Appl*, vol. 40, no. 9, pp. 3828–3840, Jul. 2013, 10.1016/j.eswa.2012.12.097.
- [43] J. Milutinović, D. Marković, B. Stanivuković, L. Švadlenka, M. Dobrodolac, "A model for public postal network reorganization based on DEA and fuzzy approach," *Transport*, vol. 35, no. 4, pp. 401–418, Oct. 2020, 10.3846/transport.2020.13741.
- [44] T. A. Yanar and Z. Akyürek, "Fuzzy model tuning using simulated annealing," *Expert Syst Appl*, vol. 38, no. 7, pp. 8159–8169, Jul. 2011, 10.1016/j.eswa.2010.12.159.
- [45] O. Castillo and P. Melin, "Optimization of type-2 fuzzy systems based on bio-inspired methods: A concise review," *Inform Sciences*, vol. 205, pp. 1–19, Nov. 2012, 10.1016/j.ins.2012.04.003.
- [46] D. Karaboga "An Idea Based on Honey Bee Swarm for Numerical Optimization," Technical Report-TR06, Kayseri: Erciyes University, Engineering Faculty, Computer Engineering Department, 2005, [Online] Available: <https://pdfs.semanticscholar.org/015d/f4d97ed1f541752842c49d12e429a785460b.pdf>
- [47] T. Chaiyatham, I. Ngamroo, S. Pothiya, and S. Vachirasricrikul, "Design of optimal fuzzy logic-PID controller using bee colony optimization for frequency control in an isolated wind-diesel system," In *2009 Transmission & Distribution Conference & Exposition: Asia and Pacific*, pp. 1–4, 2009, 10.1109/TD-ASIA.2009.5356804.
- [48] H. Habbi, Y. Boudouaoui, D. Karaboga, and C. Ozturk, "Self-generated fuzzy systems design using artificial bee colony optimization," *Inform Sciences*, vol. 295, pp. 145–159, Feb. 2015, 10.1016/j.ins.2014.10.008.
- [49] M. Konar and A. Bagis, "Performance comparison of Particle Swarm Optimization, Differential Evolution and Artificial Bee Colony algorithms for fuzzy modelling of nonlinear systems," *Elektron Elektrotech*, vol. 22, no. 5, pp. 8–13, Oct. 2016, 10.5755/j01.eie.22.5.16336.
- [50] P. Lučić and D. Teodorović, "Bee system: Modeling combinatorial optimization transportation engineering problems by swarm intelligence." In *Preprints of the TRISTAN IV triennial symposium on transportation analysis*, pp. 441–445, 2001.
- [51] C. Caraveo, F. Valdez, and O. Castillo, "Optimization of fuzzy controller design using a new bee colony algorithm with fuzzy dynamic parameter adaptation," *Appl Soft Comput*, vol. 43, pp. 131–142, Jun. 2016, 10.1016/j.asoc.2016.02.033.
- [52] L. Amador-Angulo and O. Castillo, "A new fuzzy bee colony optimization with dynamic adaptation of parameters using interval type-2 fuzzy logic for tuning fuzzy controllers," *Soft Comput*, vol. 22, no. 2, pp. 571–594, Jan. 2018, 10.1007/s00500-016-2354-0.
- [53] L. Amador-Angulo, O. Mendoza, J. R. Castro, A. Rodríguez-Díaz, P. Melin, and O. Castillo, "Fuzzy Sets in Dynamic Adaptation of Parameters of a Bee Colony Optimization for Controlling the Trajectory of an Autonomous Mobile Robot," *Sensors*, vol. 16, no. 9, pp. 1–27, Sep. 2016, 10.3390/s16091458.
- [54] F. Olivas, L. Amador-Angulo, J. Perez, C. Caraveo, F. Valdez, and O. Castillo, "Comparative Study of Type-2 Fuzzy Particle Swarm, Bee Colony and Bat Algorithms in Optimization of Fuzzy Controllers," *Algorithms*, vol. 10, no. 3, pp. 1–27, Aug. 2017, 10.3390/a10030101.
- [55] O. Castillo, F. Valdez, J. Soria, L. Amador-Angulo, P. Ochoa, and C. Peraza, "Comparative Study in Fuzzy Controller Optimization Using Bee Colony, Differential Evolution, and Harmony Search Algorithms," *Algorithms*, vol. 12, no. 1, pp. 1–21, Dec. 2019, 10.3390/a12010009.
- [56] P. T. Nguyen, "Construction site layout planning and safety management using fuzzy-based bee colony optimization model," *Neural Comput Appl*, vol. 33, pp. 5821–5842, Jun. 2021, 10.1007/s00521-020-05361-0.
- [57] N. Mijović, M. Kalić, J. Kuljanin, "Tuning the fuzzy logic system by two meta-heuristics: case study of airline market share on long-haul routes," *Transp Res Proc*, vol. 52, pp. 453–460, 2021, 10.1016/j.trpro.2021.01.053.
- [58] D. Teodorović "Bee Colony Optimization (BCO)," in Lim C.P., Jain L.C., and Dehuri S. (Eds.), *Innovations in Swarm Intelligence. Studies in Computational Intelligence*, pp. 39–60, Berlin: Springer, 2009, 10.1007/978-3-642-04225-6\_3.
- [59] G. Z. Marković, "Optimization of resources usage in optical wavelength routing networks," Ph.D. Dissertation, University of Belgrade, Serbia, 2007.