

# A Lane-Changing Behavioral Preferences Learning Agent with its Applications

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**Abstract.** Traditional lane-changing (LC) behavioral researches usually focus on the driver's cognitive performance which includes the driver's psychological and behavioral habit characteristics, rarely involving the affection of expert driver's comprehensive behavioral preferences, such as: safety and comfort performance in LC process. Towards the free LC process, a novel LC safety and comfort degree index is proposed in this paper, as well as, the novel definition of LC driving behavioral preferences is described in detail. Taking advantage of interactive evolutionary computing (IEC) and real-time optimization (RTO) metrics, a kind of LC behavioral preferences on-line learning agent extending traditional Belief-Desire-Intention (BDI) structure is explicitly proposed, which can perform behavioral preferences learning activities in the LC process. In addition, driving behavioral preferences learning strategies are introduced which can gradually grasp essentials in driver's subjective judgments in decision-making of the LC process and make the LC process more safety and scientific. Specifically, a conceptual model of the agent, driving behavioral preferences learning-BDI (DpL-BDI) agent is introduced, along with corresponding functional modules to grasp driving behavioral preferences. Furthermore, colored Petri nets are used to realize the components and scheduler of the DpL-BDI agents. In the end, to compare with the traditional LC parameters' learning methods (such as: the least squares methods and Genetic Algorithms), a kind of LC problems is suggested to case studies, testing and verifying the validity of the contribution.

**Keywords:** Agent, Driving behavioral preferences, Interactive learning, Colored Petri Nets (CPN).

## 1. Introduction

It is acknowledged that intelligent transportation systems (ITS) are always corresponding to multi-attribute decision-making (MADM) problems with its focus on using intelligent methodologies. The driving behavioral preferences researches are concerning with the driver's psychological and behavioral habit characteristics, which tend to be the constraints of ITS' decision-making process. Therefore, the definition of driving behavioral preferences which corresponds to the driving safety and comfort performance has not been described in detail until now.

Currently, majority of lane-changing (LC) modeling methods' researches are concerned with theoretical relevance and simulation issues. Rahman et al. conducted a detailed review and systematic comparison of existing microscopic LC models that are related to roadway traffic simulation to provide a better understanding of respective properties, including strengths and weaknesses of the LC models, and to identify potential for model improvement using existing and emerging data collection technologies [26]; Zheng comprehensively reviewed recent developments in modeling LC behavior and categorized the major LC models in the literature into two groups: models that aim to capture the LC decision-making process, and models that aim to quantify the impact of LC behavior on surrounding vehicles [39].

Therein, towards the driving safety [19][15] and comfort performance [14][23][21] assessment, the three risk indicators (time-to collision (TTC), time headway (TH), and safety margin (SM)) and some scales (such as: driving comfort scales (DCS), perceived driving abilities (PDA) scale, situational driving avoidance (SDA) scales, et al.) are respectively employed in a large scale. However, how to construct the LC decision-making problems constrained with the driving behavioral preferences still represents a challenge.

Therein, agents are effective methods to construct the human-computer interaction (HCI) model. Sardina & Padgham developed a typical BDI-style agent-oriented programming language that enhances usual BDI programming style with three distinguished features: declarative goals, look-ahead planning, and failure handling [28]. Additionally, Wu et al. presented a new-complete first-order temporal BDI logic and forest multi-agent system and shown how to characterize the forest multi-agent system by using the hierarchical structure of modules [34]. Nonetheless, there is little literature focus on establishing the LC driving behavioral preferences interactive learning agent.

In order to effectively perform human-computer interactions in the LC process, this paper proposes a novel driving behavioral preferences' definition to study the driving behavioral preference's influence on the LC process, which includes the safety and comfort performance assessment methods. A new kind of interactive driving behavioral preferences learning agent based on (Belief, Desire and Intention) BDI structures is established. Under the real-time optimization (RTO) [4][1] framework, driving behavioral preference learning algorithms are proposed in this paper. Conceptual agent models and corresponding functional modules are explicitly introduced along with preference learning algorithms. Colored Petri nets are employed to realize and analyze the agent.

The remainder of this paper is organized as follows: Section 2 reviews related researches on LC driving behavioral preferences learning. Section 3 presents the basic free LC models, as well as the proposes the free LC MADM problems. In Section 4, the definition of free LC driving behavioral preferences is proposed, as well as, the DpL-BDI agent's conceptual model with its corresponding functional modules and associated algorithms is explicitly introduced. Section 5 presents an approach of how to apply the interactive learning agents in LC process. Section 6 concludes the article and assesses the future perspectives.

## 2. Related work

In accordance with recent literatures, researches on Lane-changing (LC) process show that the development trend is being shifted from researches on the modeling and perfor-

mance assessment methods in the early period to current researches on the LC driving behavioral preferences. A lot of new technologies and intelligent optimization algorithms are widely applied to identify the parameters of LC model and the LC driving behavioral preferences, such as: the least squares methods, genetic algorithm [8] etc. This section not only summaries recently published researches on LC driving behavioral preferences but also focuses on learning methods based on human-computer interaction.

Lane-changing's model and performance- Currently, lane-changing (LC) researches become a new-emerging research issue that targets the quantitative relations of the driving process. Specifically, Laval & Leclercq introduced a framework to solve this problem using a macroscopic theory of vehicle LC inside microscopic models, as well as, in their theory, lane changes take place according to a stochastic process that has been validated in the field, and whose mean value is a function of lane-specific macroscopic quantities [17]; Jin proposed a simple model for studying bottleneck effects of LC traffic and aggregate traffic dynamics of a roadway with LC areas [9]; Jin considered weaving and non-weaving vehicles as two commodities and develop a multi-commodity, behavioral Lighthill-Whitham-Richards (LWR) model of LC traffic flow and derive a fundamental diagram with parameters determined by LC and LC characteristics as well as road geometry and traffic composition [10]; Zheng et al. proposed a neural network (NN) model to capture the complexity of LC, and large-scale trajectory data are employed for model estimation and validation [38]; Lv et al. developed an integrative traffic model, in which a method to calculate the LC probability and the merging probability was proposed [20]; Patire & Cassidy introduced a key mechanism of the vehicular LC: LC can be induced by speed disturbances (SDs) that periodically arise in the expressway's median and center lanes [25]. It is conceivable that how to comprehensively quantify the driving behavioral preferences with the safety and comfort performance in the ITS' models still remains a challenge.

Driving behavioral preferences- Alternatively, a lot of researches are concerned with the relations between driving behavior and the performance of LC process. For example, Hidas introduced the Simulation of Intelligent TRAnsport Systems (SITRAS), a massive multi-agent simulation system in which driver-vehicle objects are modeled as autonomous agents [6]; Tang et al. proposed a macroscopic model of LC that is consistent with LC behavior on a two-lane highway [31]; Tideman et al. presented a new approach for determining users' preferences and finding the best compromise between those preferences when designing a new driver support system [32]; Schubert et al. described a system that can perceive the vehicle's environment, assess the traffic situation, and give recommendations about lane-change maneuvers to the driver [29]; Peng et al. built a new cellular automaton (CA) model, based on the driving decision (DD), as well as, in the DD model, a driver's decision is divided into three stages: decision-making, action, and result [37]; Zheng et al. investigated the effects of LC in driver behavior by measuring (i) the induced transient behavior and (ii) the change in driver characteristics and the changes in driver response time and minimum spacing. Nonetheless, these researches need the large scale samples, suffering the approaches to grasp the driving behavioral preferences based evolutionary strategies [40].

HCI and Agent-Human-computer interactive (HCI) models concerning human behaviors, languages, etc. can be classified into three categories: artificial action cycle models, GOMS (Goals, Operators, Methods, and Selection rules) models, and artificial process

models [5][7][22][33]. Typically, BDI (Belief, Desire and Intention) agent models are extensively employed to demonstrate rational reasoning abilities of agents, attracting increasing attention in both academia and application fields recently. For example, Casalia et al. introduced a graded BDI agent development framework and proposed a sound and complete logical framework for it [3]. Thereafter, a lot of agent's applications [27][35][13] are developed. However, the applications rarely involved the driving behavioral preference. Meanwhile, the Petri nets are usually employed to establish agent models [18][24]. At present, little literature reported the methods in establishing the driving behavioral preferences learning agent.

Parameters identification-With the development of probe vehicle technologies and the emerging connected vehicle technologies, applications and models using trajectory data for calibration and validation significantly increase. Traditional parameters' identification based vehicle trajectory always focuses on the car-following process. Jin et al. proposed the error dynamic model based on an acceleration-based generic car-following model formulation, as well as, they explore the mechanism and countermeasures of the error accumulation problems of car-following models calibrated with microscopic vehicle trajectory data[12]; to deal with traveler behaviors in transport studies, Kim et al. proposed a rigorous methodology to calibrate a GM-type car-following model with random coefficients, which could account for the heterogeneity across drivers who respond differently to stimuli [12]. In addition, the lane changing process can be divided into two coordinates: horizontal and vertical motion model, as well as, the horizontal motion model can be regarded as a car-following process. Because the lane changing process is complex, there is little literature reports the related parameters' interactive learning methods.

Thereafter, a novel driving behavioral preferences' definition and a new kind of interactive driving behavioral preferences learning agent based on (Belief, Desire and Intention) BDI structures are proposed to study the driving behavioral preference's influence on the LC process.

### 3. The mathematical formulation of Lane-changing

#### 3.1. The free Lane-changing model

The classical free Lane-changing (LC) model (in [26][39]) is presented as follows in Fig. 1:

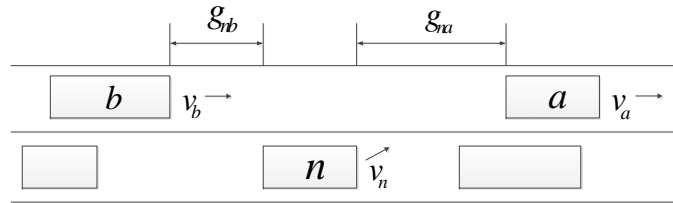
$$\begin{aligned} g_{na}^D &= \max\{g_a^D, g_a^D + \beta_{a1}^D v_n + \beta_{a2}^D (v_n - v_a) + \varepsilon_{na}\} \\ g_{nb}^D &= \max\{g_b^D, g_b^D + \beta_{b1}^D v_b + \beta_{b2}^D (v_n - v_b) + \varepsilon_{nb}\} \end{aligned}$$

Where,  $g_{na}^D$  is critical lead gap;  $g_{nb}^D$  is critical lag gap;  $g_a^D$  is minimum lead gap;  $g_b^D$  is minimum lag gap;  $v_a$  is speed of the lead vehicle;  $v_b$  is speed of the lag vehicle;  $v_n$  is speed of the lane changer;  $\beta$  are parameters,  $\varepsilon_{na}, \varepsilon_{nb}$  are error terms.

The acceleration of the lane changer is:

$$\frac{dv_{j-1}(t)}{dt} = h[v(\Delta x_j(t)) - v_{j-1}(t)] + \tau(\Delta v_j(t)) \quad (1)$$

where,  $\Delta x_j(t)$  is described as the distance between the lead car and the participant car,  $v(\Delta x_j(t))$  is an optimize real-time speed function corresponding to the distance between



**Fig. 1.** The classical free Lane-changing model

the two vehicles;  $v_{j-1}(t)$  was the speed of participant car at the time  $t$ ,  $\Delta v_j(t)$  is the relative speed of the two vehicles ( $\Delta v_j(t) = v_j(t) - v_{j-1}(t)$ ),  $h$  is the synthesized index corresponding to the safety and economy performance,  $\tau$  is the delay factor,  $j$  is the vehicle number.

Nonetheless,  $v(\Delta x_j(t))$  in the formula is described as:

$$v(\Delta x_j(t)) = \begin{cases} v_{j-1}(t)\{1 + \tanh[G(\Delta x_j(t) - h_c(t))]\} & \Delta x_j(t) < h_c(t) \\ v_{j-1}(t) + (v_{max} - v_{j-1}(t)) \cdot \tanh[G(\Delta x_j(t) - h_c(t))] & \Delta x_j(t) \geq h_c(t) \end{cases} \quad (2)$$

where,  $h_c(t)$  is described as a safe distance at time  $t$  between the two vehicles (To simplify the study,  $h_c(t)$  is defined as a constant),  $G$  and  $h$  are both dynamic unknown parameters,  $v_{max}$  is the maximum freedom speed of the participant car,  $\tanh$  is the dual music function.

**3.2. The free lane-changing multi-attribute decision-making (MADM) problems**

The free lane-changing (LC) is a kind of uncertainty MADM problems involving human-computing interaction, where human’s preferences tend to be constraints of the decision solutions. Therefore, it is necessary to discuss the decision-making mechanism based on driver’s behavioral preference interactive learning in LC process.

To solve uncertainty LC MADM problems with experiential knowledge and behavioral preferences, it is corresponding to a class of multi-attribute fuzzy mathematical programming problems. Thereafter, we can conceptually give the formal description as follows:

*OPT:*

$$OBJ_{no}(x, y) < O_{no}, no = 1, 2, \dots \quad (3)$$

*s.t.*

$$\begin{aligned} & \textit{lane-changing model} \\ & \textit{safety indicator} \\ & \textit{comfort indicator} \\ & x \in \mathbf{R}, y \in \{0, 1\} \\ & \mu_{pre}(x, y) = \textit{Driving - preference} \end{aligned}$$

Where,  $x$  and  $y$  are described as continuous and discrete operating variables ( $x \in \mathbf{R}, y \in \{0, 1\}$ );  $O_{no}(no = 1, 2, \dots)$  are key quantitative objective;  $\mu_{pre}$  is described as fuzzy membership functions corresponding to the decision-making vectors, which reflects the decision-making behavioral preferences.

#### 4. Driving behavioral preferences learning BDI (DPL-BDI) Agent

Towards the objective whose optimal values are unknown and dynamic, human usually tends to solve it by subjective experience. In addition, based on the definition of driving behavioral preferences, computer can track and learn the free LC multi-attribute decision-making (MADM) process, as well as make the driving process more personalized and comfortable.

Time to collision (TTC) [36][30] has been a key vehicle safety metric for decades. With the increasing prevalence of advanced driver assistance systems and vehicle automation, TTC and many related metrics are being applied to the analysis of more complicated scenarios, as well as being integrated into automation algorithms.

The traditional TTC index [2] is described as follows:

$$THW_n = t_{n,l1} - t_{n-1,l1} \quad (4)$$

The time headway and vehicle speed can be determined:

$$V_n = \frac{D}{(T_{n,L2} - t_{n,L1})} \quad (5)$$

Where,  $n$  refers to the vehicle identification (assigned by the order of appearance),  $L1$  is the upstream reference line,  $L2$  is the down stream reference line, and  $D$  corresponds to the distance between the two reference markings. The length of  $D$  used in this study is 15m.

The distance gap  $DX$  between two vehicles is determined by

$$DX_n = THW_n \times V_n - l_{car} \quad (6)$$

Where,

the average car length  $l_{car}$  is taken to be 4.5 m.

TTC is then estimated using

$$TTC_n = \begin{cases} \frac{DX}{DV} = \frac{DX}{v_n - v_{n-1}}, v_n > v_{n-1} \\ N.A., \textit{otherwise} \end{cases} \quad (7)$$

While the TTC metric was originally conceived to be a mandatory constraint in the car-following process, its applications rarely involving the driver's expectations for the TTC index based driving behavioral preferences within the safe consideration.

**Definition 1** (Lane-changing safety degree index):

$$SI = \frac{\sqrt{\frac{1}{N} \sum_{i=1}^N (TTC_i - \bar{TTC})^2}}{\hat{\xi}} \quad (8)$$

Where,  $i$  corresponds to the  $i^{th}$  time in the car-following process;  $TTC_i$  is the time to collision index at the  $i^{th}$  time in the car-following process;  $\bar{TTC}$  is described as the average TTC index;  $\hat{\xi}$  is the expected variance of TTC.

**Definition 2** (Lane-changing comfort degree index):

$$CI = \frac{\sqrt{\frac{1}{N} \sum_{i=1}^N (a_i - \bar{a})^2}}{\hat{\sigma}} \quad (9)$$

Where,  $i$  corresponds to the  $i^{th}$  time in the car-following process;  $a_i$  is the participation car's acceleration at the  $i^{th}$  time in the car-following process;  $\bar{a}$  is described as the average acceleration ( $a_i$ );  $\hat{\sigma}$  is the expected variance of the acceleration.

**Definition 3** (Free Lane-changing driving behavioral preferences):

Towards the dynamic free lane-changing MADM problems, driver's concern degree of safety and comfort performance are defined as driving behavioral preferences.

Driving behavioral preference is a two-tuple: *Driving - preference* =  $\{E_i, \lambda_i\}$ . Where,  $i$  is the attributes' number of the MADM problem. Only the safety and comfort degree index are discussed in this paper, so,  $i = 2$ ;  $E_i$  is described as the optimal value of each attribute in the free LC MADM problems;  $\lambda_i$  is described as the weight coefficient of each attribute in the free LC MADM problems.

## 4.1. Agent's model and function

### 4.1.1. Conceptual model

Real-time optimization (RTO) [24][12], which refers to the online optimization of a process plant, RTO attempts to optimize process performance (usually measured in terms of profit or operating cost) thereby enabling companies to push the profitability of their processes to their true potential as operating conditions change. The control problem is solved apart from the optimization problem at different frequencies and using different models.

Based on real-time optimization (RTO) [24] theory, driving behavioral preferences learning can be transformed to a class of RTO problems whose conceptual model is shown in Fig. 2.

Where, the arc in Fig. 2 corresponds to the driving behavioral preferences' model changing and evolution, while driver has more experience in the LC process. In order to learn the driver's preference based HCI, the Auto-Lane changing computer continuously track and identify the parameters of the driving behavioral preferences' model. Fig. 2 represents the driving behavioral preferences' tracking and learning process.

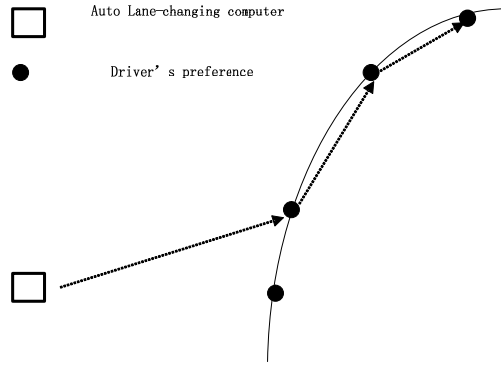


Fig. 2. Driving behavioral preferences learning conceptual model

#### 4.1.2. Driving behavioral preference learning (DpL-BDI) Agent

In regard to traditional BDI models, Belief corresponds to the information that agents have about the goal and circumstance; Desire signifies the states of affairs that agents would wish to be brought; Intention indicates the desire that agents have committed to achieve. In this sense, driving behavioral preferences interactive learning models can be considered as that the agents can constantly update the driving behavioral preference states in achieving objectives and interacting with the driver by belief, desire and intention.

In order to make the Agent have similar driving behavior and human preferences, interactive learning (L) and driving preferences (Dp) tuples are added in traditional BDI models to constitute DpL-BDI Agent model.

**Definition 4** (DpL-BDI models):

A DpL-BDI model is a five-tuple,  $DpL - BDI = \{Dp, L, B, D, I\}$ , where

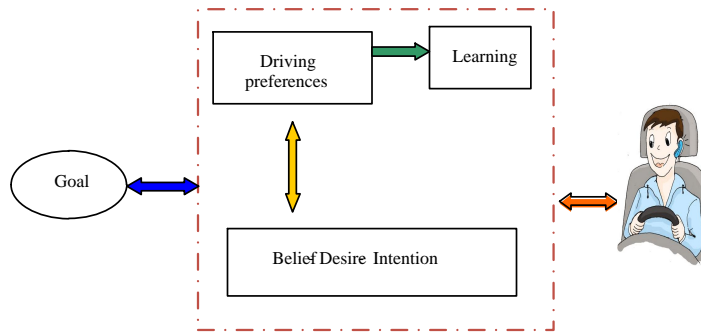
1.  $B$  is the Belief set, including the LC goals that agents wish to achieve and the related data, i.e. for  $B_i \in B$  we have  $B_i = \{[g_i, data_i | g_i \in G, data_i \in Data, ]\}$ .  $G$  is the goal set,  $Data$  is the data set;
2.  $D$  is the Desire set, including the assessments of agents' achievements and related data, i.e. for  $D_i \in D$  we have  $D_i = \{[ge_i, data_j | ge_i \in GE, data_j \in Data]\}$   $GE$  is the assessment set, is the data set;



3.  $I$  is the Intention set, including the algorithms that are employed to accommodate Belief set and Desire set, i.e. for  $I_i \in I$  we have  $I_i = \{al_i(D_i, B_i | al_i \in AL)\}$ ,  $AL$  is the algorithm set;
4.  $Dp$  is the driving behavioral preferences set, corresponding to the goals' assessment and process data, as well as identifying the parameters of driving behavioral preferences model. For  $Dp_i \in Dp$  we have  $Dp_i = \{a_i = Model(B_i, D_i, I_i)\}$ ,  $Model$  is the driving behavioral preference model; B, D and I, i.e. correspond to the interactive parameters;
5.  $L$  is the Learning set, including the driving behavioral preferences learning algorithms in response to  $B_i, D_i, I_i, DP_i$  and  $Dp_i$ , i.e. for  $L_i \in L$  we have  $L_i = \{l_i = Algorithm(B_i, D_i, I_i, DP_i)\}$ ,  $L$  is the  $L_i = \{l_i = Algorithm(B_i, D_i, I_i, DP_i)\}$  learning algorithms.

To clarify the relationship among the components of DpL-BDI models, it is imperative to investigate the expected nominal activities of the agents, which motivates the following concepts.

DPL-BDI Agent's conceptual models are shown as follows in Fig. 3.



**Fig. 3.** DpL-BDI Agent's conceptual models

#### 4.1.3. Functional modules

According to the philosophy of DpL-BDI models, a kind of driving behavioral preferences learning agent is designed to solve the LC MADM problems. In what follows, we introduce the major functional modules in turn.

**(1) Multi-attribute decision-making algorithms**

To identify the *Driving – Preferences* parameters  $E_i$  and  $\lambda_i$ , the LC problems can be formulated as a constrained nonlinear MADM statement, described as follows:

$$\begin{aligned} \text{opt. } & \begin{cases} \min SI \\ \min CI \end{cases} \\ \text{s.t. } & \begin{cases} V_{M-1}(t) \\ V_m(t) \\ V_M(t) \\ s(t) \end{cases} \end{aligned}$$

Where, the objective consists of two sub-objectives: minimum the LC safety degree and comfort degree; the constraints consist of four models: speed of the lead vehicle ( $V_{M-1}(t)$ ), speed of the lane changer ( $V_m(t)$ ); speed of the lag vehicle ( $V_M(t)$ ); the critical lead gap model  $s(t)$ . The parameters to be identified are the weight coefficient ( $\lambda_i, i = 1, 2$ ) of each attribute in this lane-changing MADM problems, as well as, the unknown parameters in the four constraint models, such as: G, H and  $\tau$  of  $V_m t$ ;  $\beta_{11}$  and  $\beta_{12}$  of  $s(t)$ .

Interactive evolutionary computing (IEC) [16][11] is a kind of evolutionary computing method that the fitness function evaluation needs human to review. In addition, IEC's other theories and operation parts are as same as the traditional evolutionary computing (such as: Genetic algorithms). Taking advantage of IEC, the procedure towards multi-attribute decision-making algorithms is presented as follows.

- Step 1: Initiate  $t = 0$  and create an initial population  $\bar{a}_t$  of candidate solutions randomly over the global searching space;
- Step 2: Specify an importance degree for each objective, and, in regard to every individual, calculate corresponding objective fitness index K based on multi-attribute assessment module;
- Step 3: Aided by agents, human operators evaluate the excellent individuals of candidate solutions in terms of fitness index K. At the same time, agents perform driving behavioral preferences computing and learning algorithms, generating evaluations of individuals for human references;
- Step 4: Select excellent individuals based on HCI;
- Step 5: Perform crossover and mutation operations to generate the offspring;
- Step 6: Decode and return to Step 2.

**(2) Multi-attribute assessment**

Considering a decision-making problem with n attributes, specify an objective fitness index as:

$$k = \sum_{i=1}^n \lambda_i \varphi_i \tag{10}$$

Where,  $\lambda_i$  is defined as the relative importance degrees of objective  $p_i$  that are constrained by  $\sum_{i=1}^n \lambda_i = 1$ ;  $\varphi_i$  is the achievement degree of  $p_i$ . For the proposed methods in this paper,  $\varphi_1 = \frac{\hat{S}I}{SI}$  and  $\varphi_2 = \frac{\hat{C}I}{CI}$ , where,  $\hat{S}I$  is the desired safety degree index,  $SI$

is the realistic safety degree, as well as,  $\hat{C}I$  corresponds to the desired comfort index,  $CI$  corresponds to the realistic comfort index.

**(3) Driving behavioral preference learning**

The aim of this module is twofold, obtaining human’s driving behavioral preferences and updating the adjustable parameters of preference computing models. Driving behavioral preferences’ learning helps agents get access to driver’s preferences towards decision making so as to learn from them, gradually replacing human’s subjective judgment and lessening human’s subjective fatigue and promoting more scientific implementations.

According to the driving behavioral preferences models, interactive learning problems can be formulated as a constrained nonlinear programming statement, described as follows.

$$\begin{aligned} \min \sum_{m=1}^n [\mu(k_m) - \mu'(k_m)]^2 (m = 1, \dots, n) \\ \text{s.t.} \begin{cases} \sum_{i=1}^2 \lambda_i = 1 \\ \tau \leq 2 \end{cases} \end{aligned} \tag{11}$$

Where,  $\mu(k_m), (m = 1, \dots, n)$  corresponds to the Agent’s performance optimal assessment sequences in lane-changing process;  $\mu'(k_m), (m = 1, \dots, n)$  correspond to the expert driver’s satisfaction degree sequences in LC process. Additionally, genetic algorithms can be invoked to solve this optimization problem whose implementing steps are shown in Fig. 4. A simplified functional structure of the DpL-BDI agents is shown in Fig. 5.

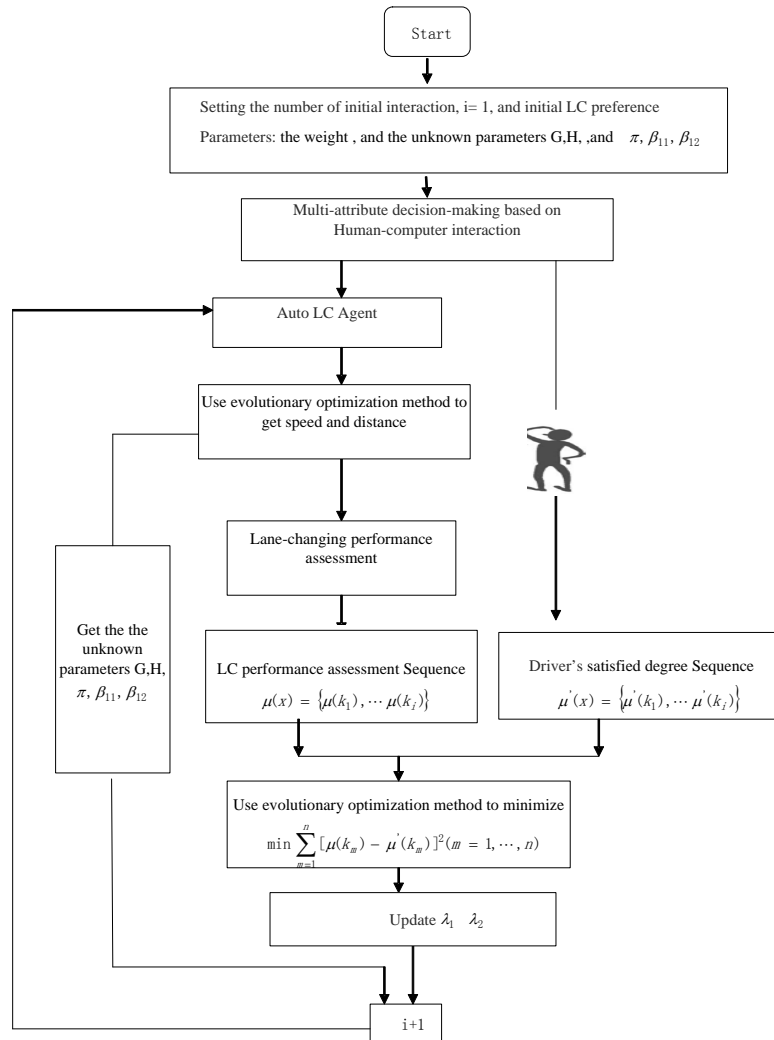
**4.2. Agent’s analysis based on Colored Petri nets**

Petri nets are used to describe the mathematical model of the parallel and discrete system, which is suitable for constructing the concurrent and asynchronous computer system model. To study the driving behavioral preference learning algorithm’s rationality and the triggering process, petri nets are employed to realize the components and scheduler of the driving behavioral preferences’ learning (DpL)-BDI agents.

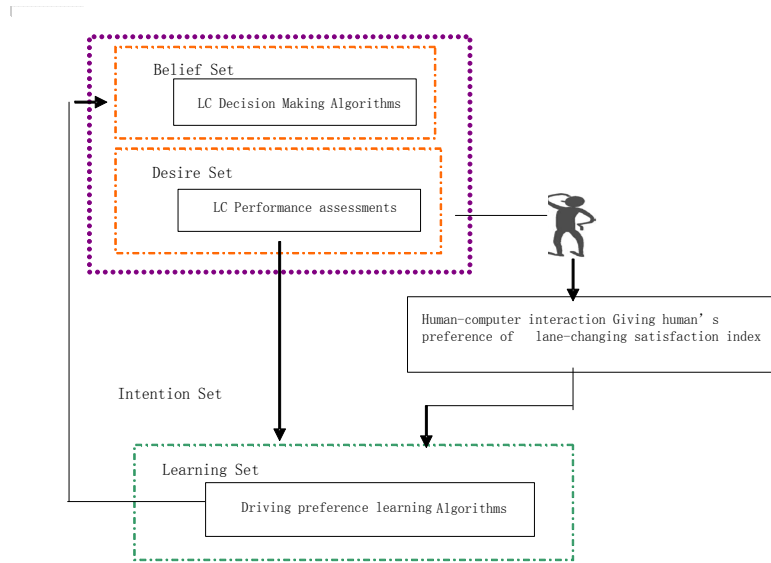
As a kind of high-level Petri net, colored Petri net (CPN) is capable of description and analysis of large and complex Agent’s systems. A well-formed CPN,  $\Sigma = (C, P, T, A, F, M)$ , is made of six components, where,  $C$  indicates color functions;  $P$  is a finite set, called place set;  $T$  is a finite set, called transition set;  $A$  is a finite set, called arc set;  $F \subseteq (P \times T) \cup (T \times P)$  is defined as the flow relationship;  $M : P \rightarrow \{0, 1, 2, 3, \dots\}$  is defined as the network functions (Marking). In this context, CPNs based DpL-BDI agents could be specified as follows.

**Definition 5** (Places of agents):

- $P_B$  is a Belief color set,
- $P_B = \{P_{B_1} \text{ (MADM algorithms)}, P_{B_2} \text{ (solutions of MADM)}\}$ ,
- $P_D$  is a Desire color set,
- $P_D = \{P_{D_1} \text{ (multi-attribute fitness index algorithms)}, P_{D_2} \text{ (multi-attribute fitness index values)}\}$ .
- $P_I$  is an Intention color set,



**Fig. 4.** Driving behavioral preferences' learning algorithms



**Fig. 5.** Functional structure of the DP-L BDI agents

$P_I = \{ P_{I_1} \text{ (LC assessment index algorithms)}, P_{I_2} \text{ (Agent's assessment index sequence)} \}$ .

$P_{Dp}$  is a driving behavioral preferences' color set,

$P_{Dp} = \{ P_{Dp_1} \text{ (Human-computer interaction)}, P_{Dp_2} \text{ (Driver's satisfied degree index sequence)} \}$ .

$P_L$  is a driving behavioral preferences' learning color set,

$P_L = \{ P_{L_1} \text{ (Preferences' learning algorithms)}, P_{L_2} \text{ (updated parameters } \lambda_1, \lambda_2) \}$ .

CPN-Tools software is originally developed by the CPN Group at Aarhus University from 2000 to 2010. The tool features incremental syntax checking and code generation, which take place while a Petri net is being constructed. We could in turn build all functional modules of agents by CPN metrics. As an exemplary case, the scheduling model for functional modules of agents is presented based on CPN-Tools software in Fig. 6, as well, in which the associated notations are interpreted in Table 1.

## 5. Case studies

The integrated LC driving behavioral preferences learning experiments are presented in this paper. Three contrast experiments are constructed to identify the driving behavioral preferences' parameters by the least squares methods, the traditional GA algorithms and the methods proposed in this paper, as well as, the results' discussion is given in this section.

**Table 1.** Interpretations of places and transitions associated with the CPN models

Place	Color Set	Messages	Transition	Messages
p1 (mode1sta)	Model of the Agent's goal	LC math models ready	T1	Executing the interactive decision making algorithms
p2 (PB1sta)	State of the first component in Belief set	Multi-attribute decision-making algorithms ready	T2	Executing the LC performance fitness index computation algorithms
p3 (PB2sta)	State of the second component in Belief set	Achievement of a set of evolutionary solutions	T3	Sending the fitness index
p4 (PD1sta)	State of the first component in Desire set	LC performance fitness index computation algorithms ready	T4	Interacting
p5 (PD2sta)	State of the second component in Desire set	Accomplishment of the multi-attribute fitness index	T5	Executing the interactive preference learning algorithms
p6 (PI1sta)	State of the first component in Intention set	Transferring commands		
p7 (PI2sta)	State of the second component in Intention set	Agent's assessment index sequence ready		
p8 (PDp1sta)	State of the first component in Driving behavioral preference set	Interaction		
p9 (PDp2sta)	State of the second component in Driving behavioral preference set	Driver's satisfied degree index sequence ready		
p10 (PL1sta)	State of the first component in Learning set	Interactive preference learning algorithms ready		
p11 (PL1sta)	State of the second component in Learning set	Update of the preference parameters $\lambda_1, \lambda_1$		

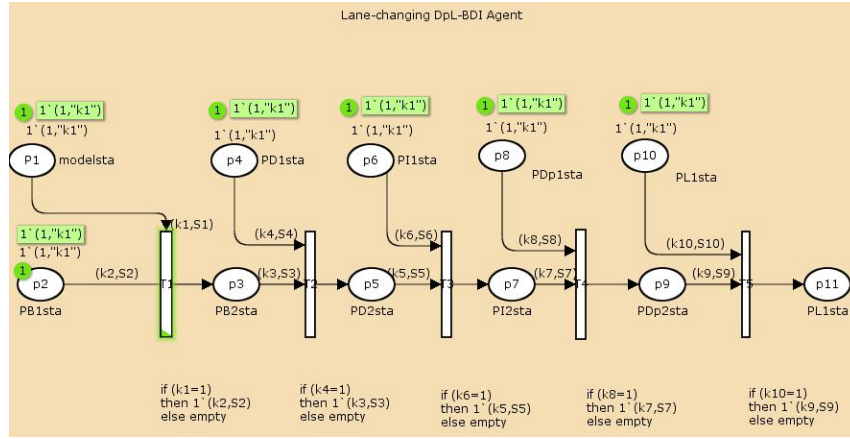


Fig. 6. Scheduling model for functional modules of agents

5.1. The least squares methods

In the experiments, traffic simulation software Q-Paramics v6.9.3 and VC++6.0 are employed to build the experimental platform in this paper. Paramics was developed for microscopic traffic simulation by the British company Quadstone, as well as, it provided a new-computational tool for the traffic engineers and researchers to understand and analyze the real conditions. Thereafter, a two-way road network model is established, including some constraint such as the road length is 80km, the maximum speed is 120km/h, there're two intersections on the network.

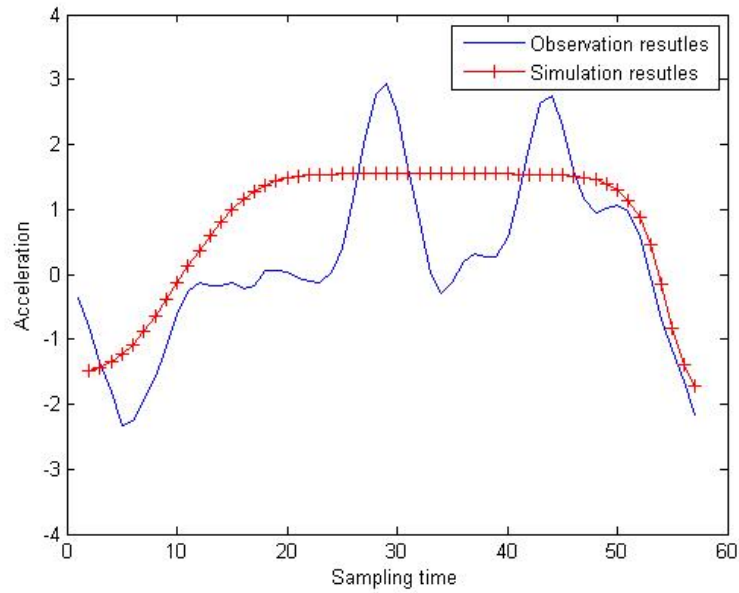
The total simulation time is defined as 30s; the sampling time is defined as 0.5s. The experimental data consists of vehicle number, road number, the speed of following the vehicle, the forward vehicle number, headway, and the speed of the forward vehicle.

The least square methods are the most commonly traffic trajectory model parameters' identification method in the LC process [13]. Based on the optimization model and the experimental data (the lane changer is a car, the lead vehicle is a car), Fig. 7 shows the fitting curve of the acceleration in the LC process.

5.2. Traditional GA algorithms

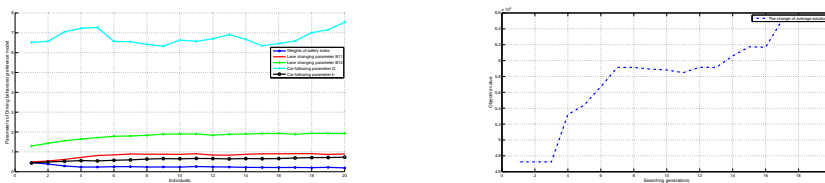
To analyze the LC driving behavioral preference parameters' difference between different types of vehicles, three common vehicles are selected in this experiment, such as: cars, buses and trucks. Based on the Q-Paramics software, nine LC scenes are performed in this paper, such as: (the lane changer is a car, the lead vehicle is a car; the lane changer is a car, the lead vehicle is a truck; the lane changer is a car, the lead vehicle is a bus; the lane changer is a truck, the lead vehicle is a car; the lane changer is a truck, the lead vehicle is a truck; the lane changer is a truck, the lead vehicle is a bus; the lane changer is a bus, the lead vehicle is a car; the lane changer is a bus, the lead vehicle is a truck; the lane changer is a bus, the lead vehicle is a bus).

Along with software Paramics, human-computer interactive evolutions are being performed. Based on the experimental data and the traditional GA algorithms, we specify



**Fig. 7.** The fitting curve of the acceleration

20 generations and 40 individual species to identify the parameters in driving behavior preference LC model. The performances of nine LC scenes are shown in figures 8-16 respectively. Fig 17 shows the fitting curve of the acceleration in the LC process (the lane changer is a car, the lead vehicle is a car). In addition, Table 2 presents key data associated with the interaction.



(a) A (parameters' evolution of the preference and the acceleration model)

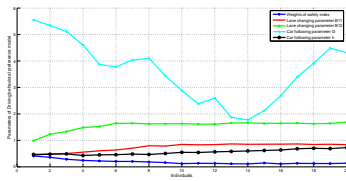
(b) B (Objective value's evolution)

**Fig. 8.** The profiles of parameters' evolution (the lane changer is a car, the lead vehicle is a car)

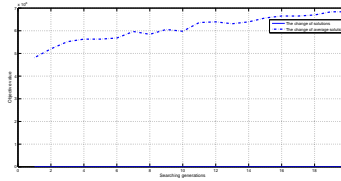
### 5.3. Using the proposed methods

Along with the proposed driving behavioral preference learning algorithms, human-computer interactive evolutions are being performed. Thereafter, a two-way road network model is



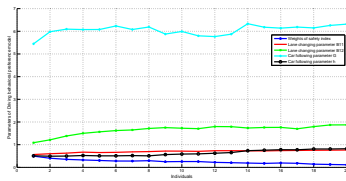


(a) A (parameters' evolution of the preference and the acceleration model)

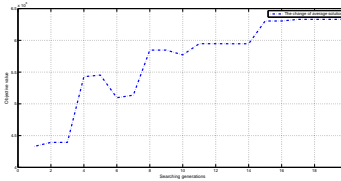


(b) B (Objective value's evolution)

**Fig. 9.** The profiles of parameters' evolution (The lane changer is a car, the lead vehicle is a truck)

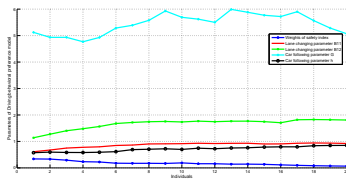


(a) A (parameters' evolution of the preference and the acceleration model)

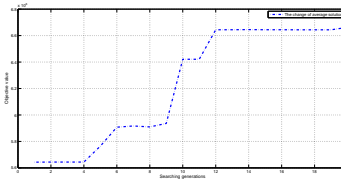


(b) B (Objective value's evolution)

**Fig. 10.** The profiles of parameters' evolution (The lane changer is a car, the lead vehicle is a bus)

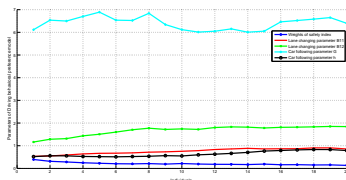


(a) A (parameters' evolution of the preference and the acceleration model)

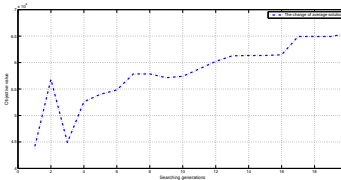


(b) B (Objective value's evolution)

**Fig. 11.** The profiles of parameters' evolution (The lane changer is a truck, the lead vehicle is a car)

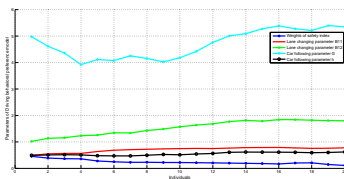


(a) A (parameters' evolution of the preference and the acceleration model)

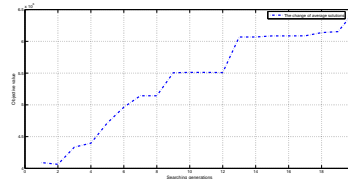


(b) B (Objective value's evolution)

**Fig. 12.** The profiles of parameters' evolution (The lane changer is a truck, the lead vehicle is a truck)

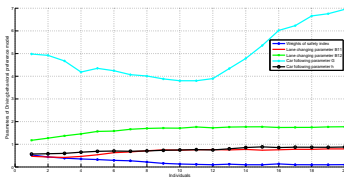


(a) A (parameters' evolution of the preference and the acceleration model)

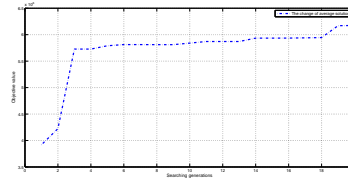


(b) B (Objective value's evolution)

**Fig. 13.** The profiles of parameters' evolution (The lane changer is a truck, the lead vehicle is a bus)

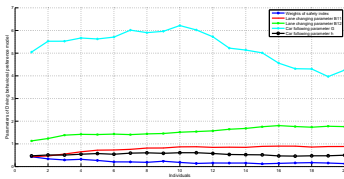


(a) A (parameters' evolution of the preference and the acceleration model)

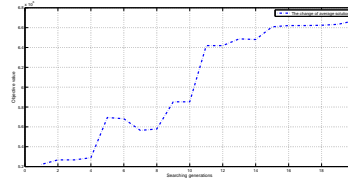


(b) B (Objective value's evolution)

**Fig. 14.** The profiles of parameters' evolution (The lane changer is a bus, the lead vehicle is a car)

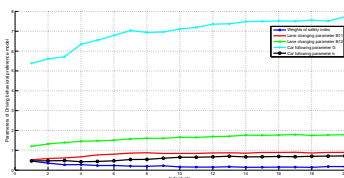


(a) A (parameters' evolution of the preference and the acceleration model)

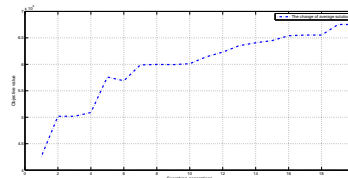


(b) B (Objective value's evolution)

**Fig. 15.** The profiles of parameters' evolution (The lane changer is a bus, the lead vehicle is a truck)



(a) A (parameters' evolution of the preference and the acceleration model)

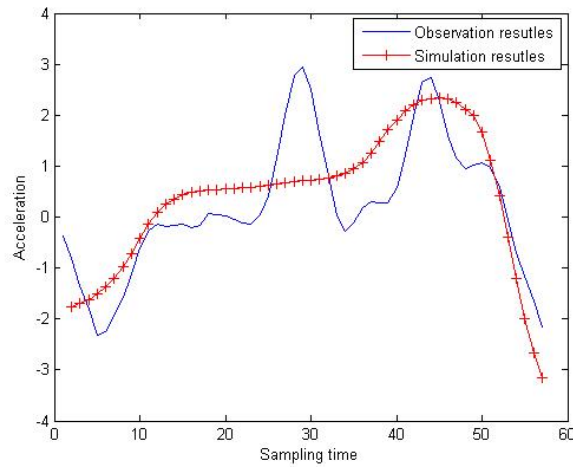


(b) B (Objective value's evolution)

**Fig. 16.** The profiles of parameters' evolution (The lane changer is a bus, the lead vehicle is a bus)

**Table 2.** Key data associated with the interaction

The lane changer	The lead vehicle	$\lambda_1$	$\lambda_2$
Car	Car	0.23	0.77
Car	Truck	0.25	0.75
Car	Bus	0.31	0.69
Truck	Car	0.21	0.79
Truck	Truck	0.20	0.80
Truck	Bus	0.19	0.81
Bus	Car	0.18	0.82
Bus	Tuck	0.19	0.81
Bus	Bus	0.21	0.79



**Fig. 17.** The fitting curve of the acceleration  
 (Based on the experimental data in 4.1 (the lane changer is a car, the lead vehicle is a car))

established, including some constraint such as the road length is 80km, the maximum speed is 120km/h, the minimum critical lag gap is 150m. In this experiment, the lane changer and the lead vehicle are both cars. Speed model of the lead car is defined as  $|50 \times \sin(\pi t)|$ .

Specify ten generations and eight individual species The performances of initial, third and the last generation are shown in Figures 18, 19 and 20 respectively. In each figure, the first line displays eight speed individuals of the lead car; the second line corresponds to 8 speed individuals of the lane changer, as well as, the third line corresponds to the multi-attribute assessment index(formula (4)). In addition, Table 3 presents key data associated with the interaction. The expected  $SI$  index (which is  $\hat{SI}$  in the formula (4)) is described as 5, as well as, the expected  $CI$  index (which is  $\hat{CI}$  in the formula (4)) is described as 2. In the end, using the same experimental data of section 4.1 (the lane changer is a car, the lead vehicle is a car), the fitting curve is shown in Fig. 21.

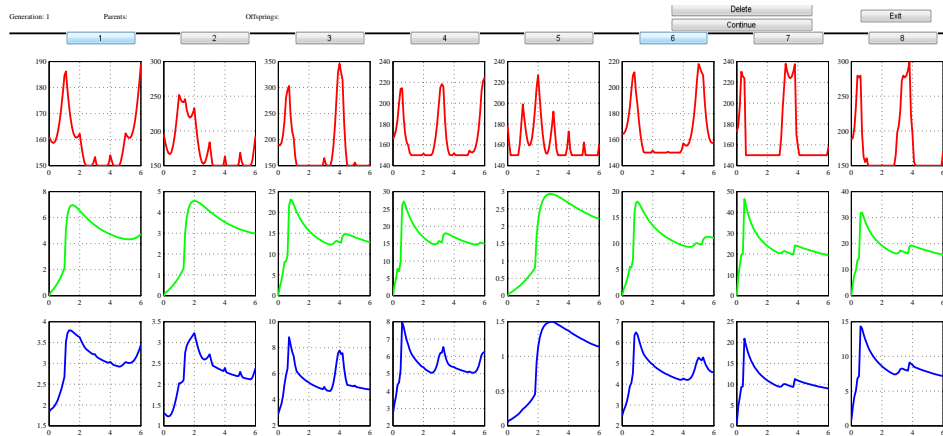


Fig. 18. Objectives of the initial population

Table 3. Key data associated with the interaction

Interaction Number	$\lambda_1$	$\lambda_2$
1	0.235	0.765
2	0.248	0.752
3	0.273	0.727
4	0.296	0.704
5	0.303	0.697
6	0.312	0.688
7	0.335	0.665
8	0.339	0.661
9	0.343	0.657
10	0.345	0.655

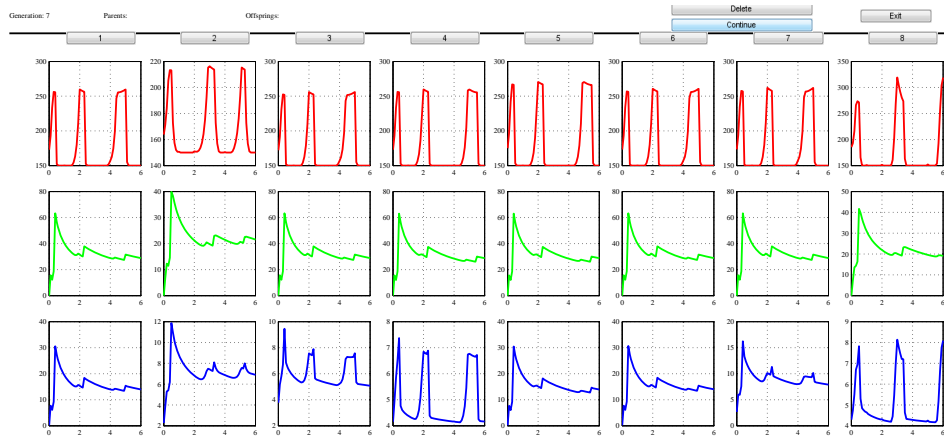


Fig. 19. Objectives of the 7th population

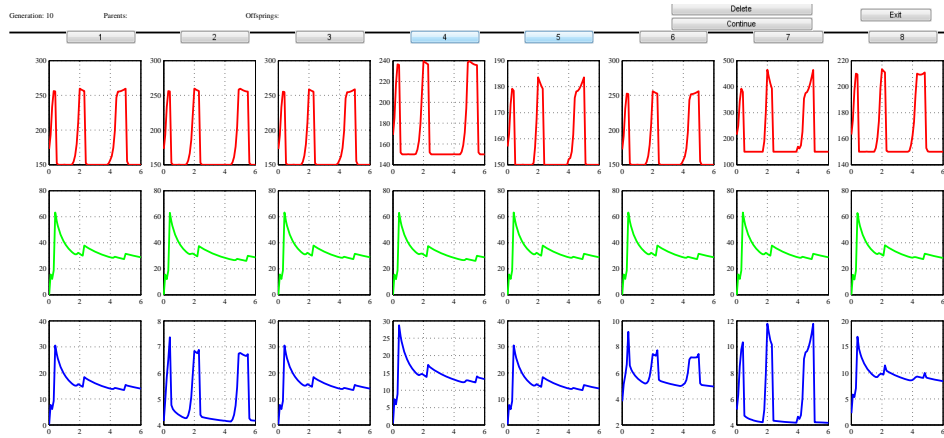
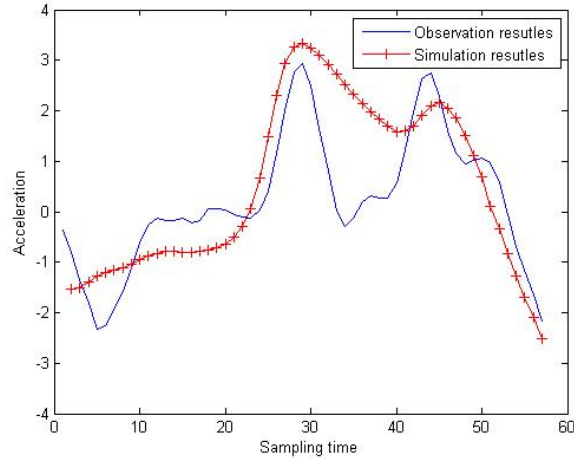


Fig. 20. Objectives of the 10th population



**Fig. 21.** The fitting curve of the acceleration

#### 5.4. Discussion

Based on the three experiments in section 5.1-5.3, we can get the analysis results as follows:

Towards a kind of LC scene, the traditional least squares methods are used to identify the LC model parameters. Because the LC model is nonlinear seriously, the fitting effect of acceleration is not good (Fig. 7).

In order to reflect the different driving behavioral preferences in the different LC scenes, GA is used to get the driving preferences for nine cases based on Q-Params. In addition, Fig. 17 is compared with Fig. 8 to verify that GA is better than the traditional least square methods in fitting the LC process acceleration curve based on the same data in section 5.1.

Finally, we design a kind of LC scene, give the lead car's velocity equation and set the corresponding LC constraints. Based on the proposed method, we obtain the driving behavioral preferences and the LC model parameters within finite interactions. Fig. 21 shows the best fitting effect of LC acceleration based on the same data in section 5.1.

It's obviously that all the traditional optimization process (the least squares methods and GA) requires historical data which is suffering the flexibility and speediness.

In addition, the proposed driving behavioral preferences' learning algorithms do not decrease the parameters' identification accuracy, as well as, they also have the 'online-learning' characteristics. The complexity of the algorithms does not increase.

## 6. Conclusions

In order to provide agents with ability of learning driving behavioral preferences towards MADM, the interactive learning mechanism has been integrated into traditional agent's

BDI models. In contrast to the traditional free LC model, the proposed preferences models are recognized capable of gradually grasping essentials in driver's subjective judgment in decision-making, as well as helping drivers make decisions more objective and scientific. Additionally, colored Petri nets are employed to build driving behavioral preferences (DpL)-BDI agent' model, as well as, the learning algorithm's logic is correct based on the CPN-Tools software. The proposed driving behavioral preferences' learning algorithms do not decrease the parameters' identification accuracy, as well as, they also have the 'online-learning' characteristics. To exemplify applications of the approaches, a kind of LC problem is suggested to case studies, giving rise to satisfied results and showing validity of the contribution.

Furthermore, it should be pointed out that this research remains rather fundamental currently, which is in desperate need of further investigations on some key issues, such as: how to record the driver's preference information, how to design more complex LC model and how to realize the driving behavioral preferences learning algorithms with the wireless vehicle communication equipment in the multi-vehicle environment.

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