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Article

Ethical and Legal Dilemma of Autonomous Vehicles: Study on Driving Decision-Making Model under the Emergency Situations of Red Light-Running Behaviors

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Abstract: Autonomous vehicles (AVs) are supposed to identify obstacles automatically and form appropriate emergency strategies constantly to ensure driving safety and improve traffic efficiency. However, not all collisions will be avoidable, and AVs are required to make difficult decisions involving ethical and legal factors under emergency situations. In this paper, the ethical and legal factors are introduced into the driving decision-making (DDM) model under emergency situations evoked by red light-running behaviors. In this specific situation, 16 factors related to vehicle-road-environment are considered as impact indicators of DDM, especially the duration of red light (RL), the type of abnormal target (AT-T), the number of abnormal target (AT-N) and the state of abnormal target (AT-S), which indicate legal and ethical components. Secondly, through principal component analysis, seven indicators are selected as input variables of the model. Furthermore, feasible DDM, including braking + going straight, braking + turning left, braking + turning right, is taken as the output variable of the model. Finally, the model chosen to establish DDM is the T-S fuzzy neural network (TSFNN), which has better performance, compared to back propagation neural network (BPNN) to verify the accuracy of TSFNN.

Keywords: autonomous vehicles; driving decision-making model; the emergency situations; red light-running behaviors; ethical and legal factors; T-S fuzzy neural network

1. Introduction

Research on autonomous vehicles (AVs) has examined social and technological trends in the development of future vehicles for their potential value. Strategic innovations in AVs could dramatically reduce congestion, emissions, traffic accidents, and the number of vehicles [1]. Furthermore, autonomous driving technology liberates humans from the driving task and significantly eliminates operation error caused by humans. Equipped with an intelligent system, AVs will complete attentive and precise tasks, including environment perception, decision-making, motion-planning, control, and execution [2]. Among them, decision-making systems have the capability to deal with complex decision environments and involve the layout of mathematical models [3]. Combined with comprehensive cognitive sequence activities, it is required for AVs to design a driving decision-making (DDM) model to form a prompt and accurate driving strategy. Taking the driver's behavior characteristic as the core, the micro-model, such as braking and lane-changing as the carrier, and the driver's behavior decision-making is modeled by machine learning [4]. Consequently, DDM is established in line with human driving habits. It is a key technology for the implementation of AVs and the advanced driver assistant systems (ADAS).

Nevertheless, at present, DDM of AVs are mainly focused on normal driving situations [5] to avoid collisions. DDM systems are usually affected by many elements, such as humans, vehicles, roads, and environments [6]. One particular challenge is the limitation of pattern recognition and obstacle detection, especially in most cases due to dead zones, object transparency, light reflection, weather conditions, and sensor failure [7]. Therefore, some collisions are bound to happen under emergent dangerous situations, which are defined as emergency situations. However, little research is focused on DDM under emergency situations.

The design of DDM under emergency situations is faced with ethical and legal dilemmas. AVs should reduce traffic accidents and avoid losses, but they will have to choose one between two evils, such as hitting a barrier and killing passengers to protect pedestrians or protecting passengers at the sacrifice of pedestrians [8]. The "trolley problem", a typical case of decision-making under emergency situations, has rapidly becoming the most recognizable scientific example of ethical and legal situations, where individuals must decide whether to change the direction of a trolley that will sacrifice one person to spare five passengers [9–11]. It is difficult for human beings to reach consensus in decision-making when dealing with sacrificial dilemmas. In addition, AVs must obey the law. However, there are few legal documents for AVs, and even fewer judge the liability of AVs in traffic accidents. With more and more AVs on our roads, how to judge liability and who is scheduled to be held responsible in case of traffic accidents must be decided, which involves not only legal questions, but also moral ones [12]. Therefore, liability directly affects the design of DDM under emergency situations. On the other hand, the use of machine learning techniques in ethics and legal dilemmas concentrates on discriminating rules and principles that are often left implicit or obscured in controversy involving ethical philosophy, psychology, and legal rule [13]. How to integrate the ethical and legal factors into the DDM of AVs which accords with human-like decision-making mechanism is a difficult problem requiring an urgent solution.

Bandana et al. [14] took full account of the legal factors in the process of lane-changing for AVs and used a fuzzy controller to convert traffic rules into logical ones to control AVs, avoiding obstacles without violating traffic regulations. Sarah et al. [15] studied lane-change decision-making when AVs encountered obstacles. They took the comfort degree of the occupant as the ethical factor in the model predictive control (MPC) and verified the cost function decision model by the experiment. Furthermore, Goodall [16] proposed a three-stage strategy to standardize the ethical decision-making behavior of AVs. The determined criteria for collision evaluation (such as death is more serious than injury) were formed by ethics. Then, the results of the simulated collision test were combined with the neural network for machine learning. The internal knowledge of the neural network was transformed into an extractable rule to improve DDM. In addition, Iyad Rahwan, a cognitive scientist at the Massachusetts Institute of Technology, conducted an online test called "Moral Machines" [17] to study the effects of ethics on driving behavior, observing people's choices for different emergency situations.

At present, much research uses neural network [18–20], decision tree model [21], support vector machine regression [22], fuzzy set theory [23], expert system [24] and Petri net [25] to establish DDM to study knowledge acquisition and presentation. Among them, neural networks are the most widely used and successful learning algorithms to establish DDM. Neural networks have many advantages, such as parallel computing, distributed information storage, fault tolerance, adaptive learning, and so on. However, it is not suitable for representing rule-based knowledge. Meanwhile, fuzzy logic is a process of uncertain and nonlinear reasoning. It is more suitable to express fuzzy and qualitative knowledge. Its reasoning mode is more similar to human thinking. However, generally speaking, it is not easy to achieve the function of adaptive learning. To sum up, the fuzzy neural network combines the knowledge configuration of fuzzy logic and the self-study ability of neural network, so it has the ability of uncertainty reasoning and self-study [26]. Combined with the advantages of artificial neural network and fuzzy system, Takagi-Sugeno fuzzy neural network (TSFNN) is chosen to establish DDM in this paper. On the one hand, the parameters in TSFNN have clear physical meaning, and can be assigned according to human experience, thus greatly improving the convergence rate. On the other hand, it is simple to compute, which makes it handle large amounts of training samples well. Meanwhile, it has strong adaptive ability to constantly correct parameters through self-learning. In addition, in the research of DDM, TSFNN is widely used for obstacle avoidance control of intelligent vehicles [27,28].

Previous research has failed to study DDM by ethical or legal factors under emergency situations, which remains at the theoretical stage. In addition, the above study only considered either the ethical or legal factor, both of which have a significant impact on DDM and cannot be ignored.

Only when the ethical or legal factors are used in a specific situation can we judge whether DDM is consistent with the code of ethics and also legal. Therefore, in this paper, we take the emergency situation evoked by red light-running behaviors as an example. In addition, ethical or legal factors are described as the specific quantitative indicators in the situations by human drivers using a questionnaire.

Specifically, this study makes the following contributions:

- In this specific scene, DDM under the emergency situation is subtly proposed, combined with ethical and legal analysis.
- Quantitative ethical and legal factors are represented by specific indicators under emergency situations of red light-running behaviors. The duration of red light (RL), the type of abnormal target (AT-T), the number of abnormal target (AT-N) and the state of abnormal target (AT-S) are chosen to represent the ethical and legal factors.
- TSFNN model is developed to accomplish the inherent complex driving decisions, including braking + going straight, braking + turning left, braking + turning right. By analyzing the experimental data, TSFNN has better performance, compared to BPNN, for establishing DDM.

The remainder of the paper is organized as follows: Section 2 introduces the emergency situations of red light-running behaviors. In addition, the decision-making in this situation is analyzed by the dimensions of ethics and law. Section 3 presents the DDM involving ethical and legal factors. In Section 4, a virtual decision-making experiment is designed to provide samples for DDM. In addition, the validity of the model is verified by analyzing the experimental data. Finally, the conclusion is drawn in Section 5.

2. Analysis of the Emergency Situations

2.1. Definition of the Emergency Situations of the Red Light-Running Behaviors

In this paper, the emergency situations of red light-running behaviors particularly refer to where abnormal targets (pedestrians, non-motor vehicles, pets, etc., collectively regarded as "abnormal target") continue to pass through a crosswalk, even though the RL is on in the crosswalk of the intersection. In this process, the avoidance space caused by the sudden entry of an abnormal target is insufficient. Therefore, a collision cannot be avoided under the emergency situations. A typical case is shown in Figure 1. We regard the blue vehicle as the AV. At this scene, the RLs are on for the crosswalk and left-turn lane. The left view of the AV is obstructed by the left turn-waiting green bus, thus the abnormal target fails to be detected in advance by the blue vehicle. It is about to encounter the emergency situation.

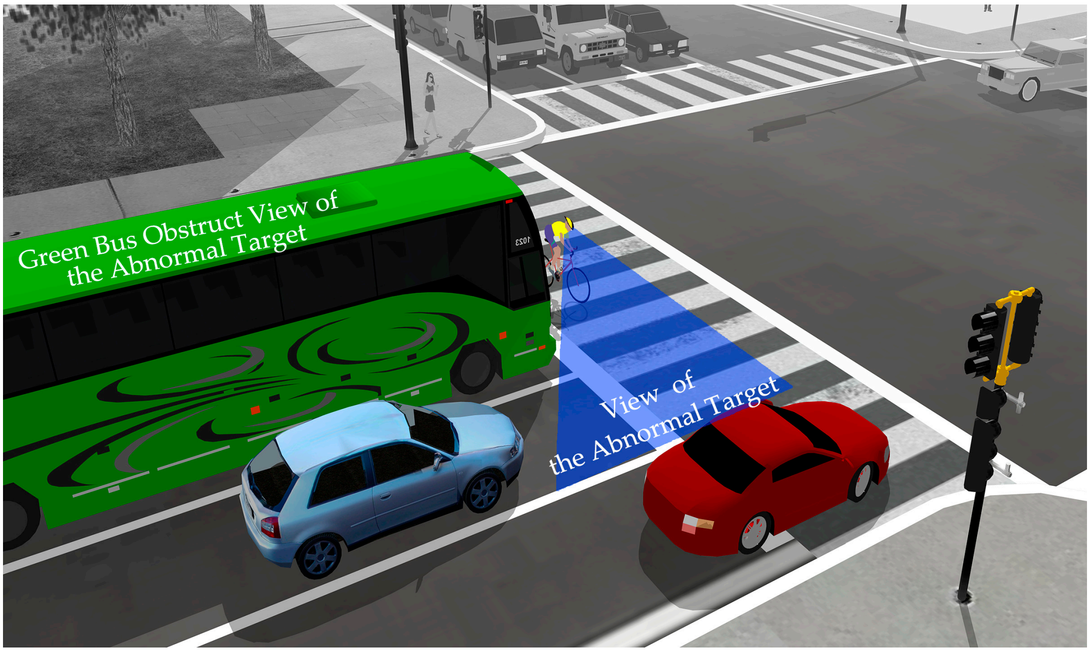

Figure 1. Typical emergency situation.

2.2. Analysis the Ethical Factor of DDM

Ethics refers to the norms of people's internal values and external behavior [29]. To behave like a human being, it is necessary for a module to interpret ethics and morality into indicators by machine learning. Based on the statistical analysis of hundreds of questionnaires in "Moral Machines" and combined with the specific scene of the emergency situations, the ethical indicators of DDM are classified into the following four types.

- Type of Abnormal Target: refers to the types of targets in front of AVs under emergency situations, which are divided into human beings, animals, and transportation facilities. Meanwhile, human beings can be further subdivided into age, gender, and physical condition and so on.
- Number of Abnormal Target: refers to the number of targets in front of AVs under emergency situations. In addition, a survey [8] shows that saving more lives is a significant factor in DDM. Decision-making made by human drivers will change dramatically as the number of rescue targets changes.
- Special State of Abnormal Target: refers to prominent features that distinguish a target from an ordinary person, such as thieves, pregnant women, tramps, etc., as well as people violating the law (red light-running or reverse driving).
- Priority Protection: The principle of priority protection in driving decision can be divided into protecting the passengers and personnel inside the vehicle, protecting the pedestrians outside the vehicle, or reducing the total loss of the collision and so on. AVs may avoid harming several pedestrians by swerving to sacrifice one pedestrian or be faced with the dilemma of sacrificing its own passenger to save one or more pedestrians.

In fact, if all the above indicators are considered, the dimensions are sizable, and the complexity of DDM will be dramatically increased. At the same time, differences in individual cognition will cause considerable controversy in the selection of specific indicators. Therefore, we select the first two indicators for the study. Referring to German ethical principles of AVs [30], we define selection principles of ethical factors as follows: distinguish pedestrians, non-motorized vehicles, and pets; do not distinguish pedestrian's age, gender, race, or body condition; do not distinguish brand, value of vehicles; do not distinguish breed of pets.

2.3. Analysis the Legal Factor of DDM

Under emergency situations, drivers will take full account of their own liability when making decisions. In China, due to a lack of legal documentation to deal with AV traffic accidents, we take existing legal documents as the basis for the legal analysis of the traffic accident liability judgment.

Traffic accident liability judgment of colliding with the abnormal target while going straight is as follows:

Referring to a real case of "red light-running behaviors" [31], we feature the detail of traffic accident liability judgment which is mainly related to the type (AT-T), state (AT-S), position of the abnormal target as well as the duration of RL through the crosswalk.

1. In case of the emergency situations, if the RL comes on and the abnormal target has passed the central line of the crosswalk, the driver has an obligation to avoid collision;
2. If the RL has lasted for a period of time and the abnormal target fails to pass the central line of the crosswalk, the liability should be determined according to the specific situations.

Traffic accident liability judgment of colliding with the abnormal target while changing lanes is as follows:

According to the relevant legal documents in China, the lane-change decision taken by the driver under dangerous conditions is defined as an emergency risk aversion [32]. If the driver can ensure the total loss caused by changing direction and collision is smaller than that of not changing lane, the driver's lane-change decision will be allowed and the party causing the dangerous situations should bear full liability. In the actual situation, the damage caused by the collision is difficult to describe quantitatively, and traffic police departments rely more on experience to judge and make the responsibility determination. To reduce complexity, it is assumed that all lane-change decisions meet the definition of the emergency risk aversion. The results of the traffic accident liability analysis are shown in Table 1.

Table 1. The results of the traffic accident liability analysis.

<table>
<tr><th rowspan="2">Serial Number</th><th rowspan="2">RL</th><th rowspan="2">AT-T</th><th rowspan="2">AT-S</th><th rowspan="2">Location of Abnormal Target</th><th colspan="2">Liability of Drivers</th></tr>
<tr><th>Going Straight</th><th>Changing Lanes</th></tr>
<tr><td>1</td><td rowspan="5">Red light Comes on Just Now</td><td>Pedestrians</td><td>Run</td><td rowspan="5">Has Already Passed the Center Line Just Now</td><td rowspan="5" colspan="2">Above Primary Liability</td></tr>
<tr><td>2</td><td rowspan="2">Non-motor Vehicles</td><td>Hold</td></tr>
<tr><td>3</td><td>Ride</td></tr>
<tr><td>4</td><td rowspan="2">Pet</td><td>Hold</td></tr>
<tr><td>5</td><td>Not Pull</td></tr>
<tr><td>6</td><td rowspan="5">Red light Has Already On</td><td>Pedestrians</td><td>Run</td><td rowspan="5">Has Not Passed the Center Line Yet</td><td rowspan="2">Equal Liability</td><td rowspan="5">No Liability</td></tr>
<tr><td>7</td><td rowspan="2">Non-motor Vehicles</td><td>Hold</td></tr>
<tr><td>8</td><td>Ride</td><td rowspan="2">Secondary Liability</td></tr>
<tr><td>9</td><td rowspan="2">Pet</td><td>Pull</td></tr>
<tr><td>10</td><td>Not Pull</td><td>No Liability</td></tr>
</table>

3. Design of DDM

Based on the environment perception, the decision-making system is central, which analyzes logic reasoning and provides decision-making for AVs. Among them, DDM is the mathematical model of the decision-making system, which plays an important role in vehicle avoidance and conflict avoidance. Using situation information, the environment perception system will detect the emergency situation mentioned in this paper. In addition, then, the decision-making system will classify and predict the behavior of other targets in the situations by a specific classifier.

3.1. Establish of DDM

We design a set of complete processes to establish the DDM, as shown in Figure 2.

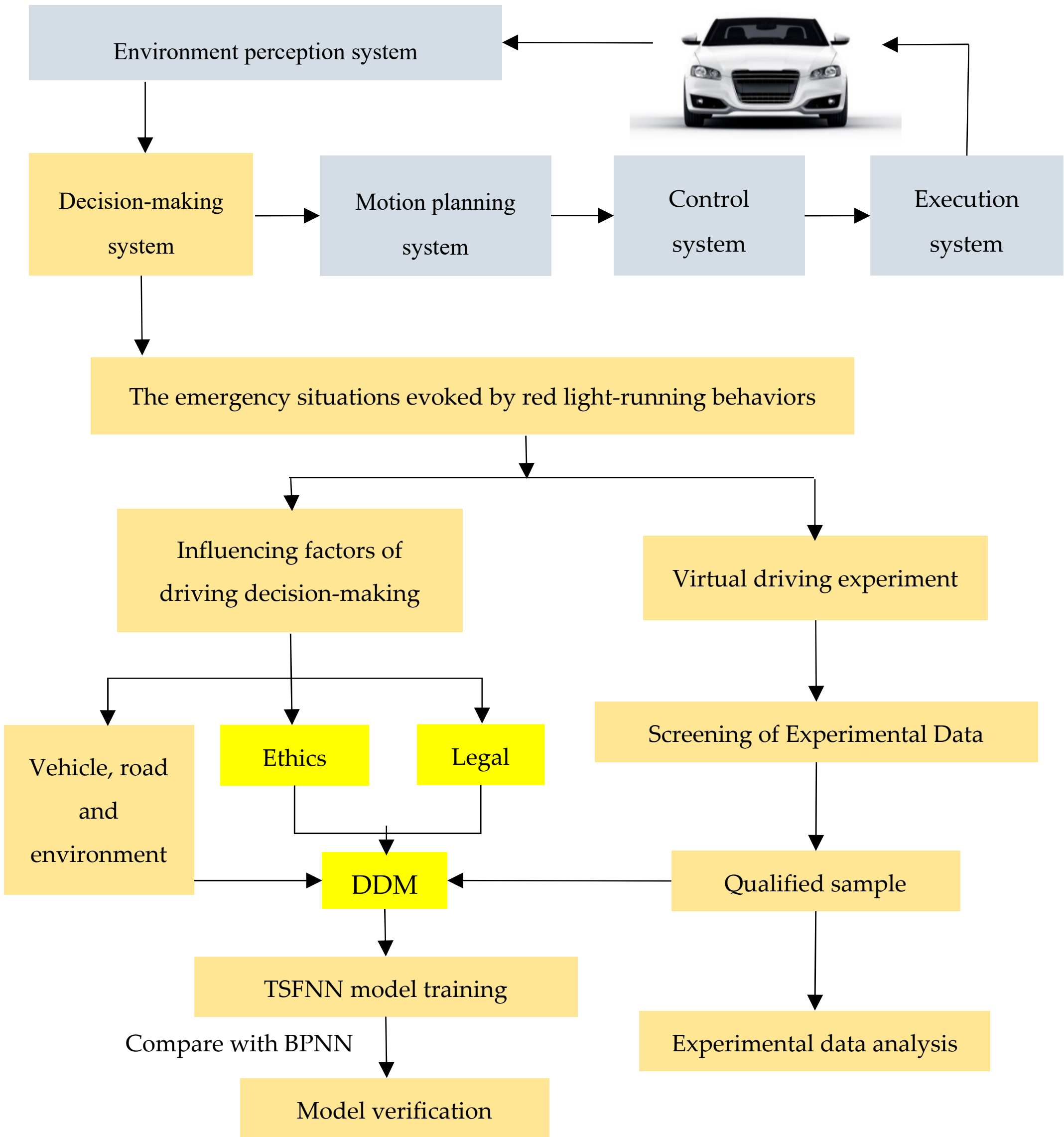

Figure 2. Design of driving decision-making model (DDM) under the emergency situations of red light-running behaviors.

DDM is supposed to have the ability to learn, so that it can be perfected during learning. Therefore, the whole process is divided into two parts. The first part is the theoretical modeling. We need to clear the impact factors of decision-making under the emergency situations of red light-running behaviors [33]. According to the analysis of Section 2, covering the conventional vehicle, road, environment, as well as ethics and law, the selected factors are regarded as the input variables of DDM, and the output variable of DDM is the driving decision-making. The second part is acquisition of the data; we designed a virtual driving experiment that reproduces the emergency situations of red light-running behaviors. The driver controls the driving simulator to complete the experiment, which provides data for the learning of DDM.

Nonetheless, in the previous analysis of ethics and law, there are still some vague concepts in the indicators to characterize driving decisions, such as some legal factors, especially the duration of RL, and how long it can take to describe a signal light that has just changed from green to red? In this paper, we will present a clear answer. Furthermore, to enable DDM to deal with fuzzy information and have the ability to learn, we build a DDM based on TSFNN and compare it with BPNN to verify the effectiveness and superiority of TSFNN.

3.2. TSFNN

A TSFNN is introduced in this paper and its structure is shown in Figure 3.

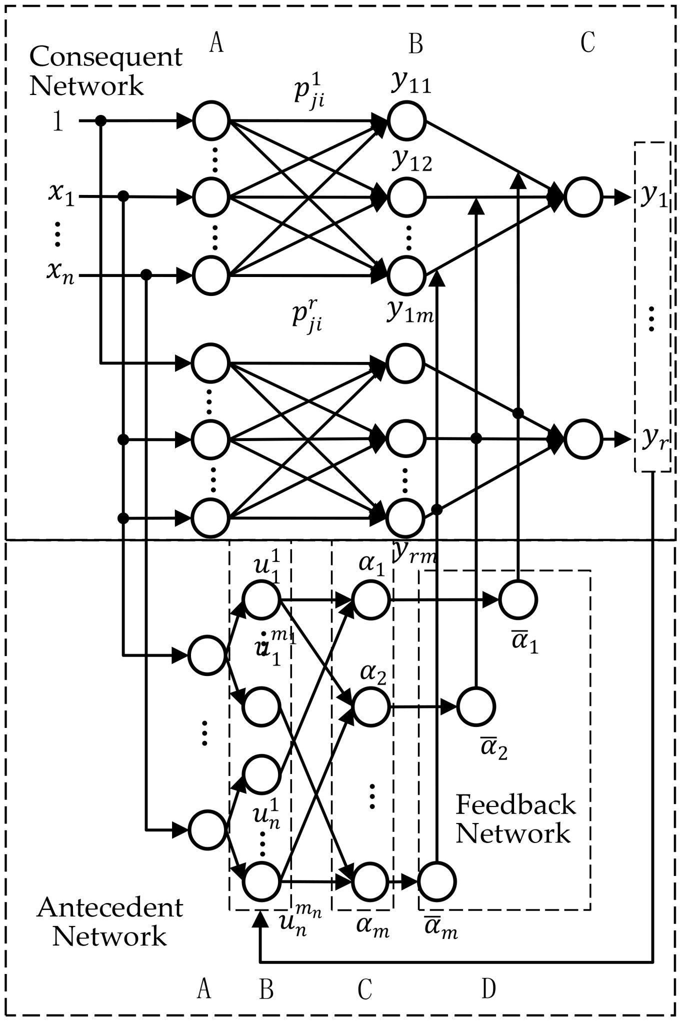

Figure 3. Structure of T-S fuzzy neural network (TSFNN).

Fuzzy neural network merges the reasoning ability of fuzzy logic system with the self-learning ability of artificial neural network. It is a powerful tool to address uncertainty and nonlinear problems. Since its fuzzy rules use a linear equation as the conclusion, in the process of dealing with multivariable systems, the number of fuzzy rules can be effectively reduced. In addition, it is easier to combine with self-adaptive method, which has been widely used in the field of intelligent control and decision-making.

The basic principle of the TSFNN is to characterize the membership degree $u_f(u)$ of each element u to the fuzzy subset f by specific numerical values, so that many fuzzy concepts can be quantitatively described. The specific rules are as follows.

Suppose $x = [x_1, x_2, \ldots, x_n]^T$ denotes an input vector, each component x_i is a fuzzy linguistic variable, then:

$$R_f : If\ x_1\ is\ A_i^j, x_2\ is\ A_2^j, \ldots, x_n\ is\ A_n^j \quad (1)$$

$$then\ y_j = p_{j0} + p_{j1}x_1 + \ldots + p_{jn}x_n \quad (2)$$

where R_j is the j^{th} fuzzy rule, A_i^j is the j^{th} linguistic value of the input variable x_i, y_i is the output variable, according to the fuzzy rule, p_{ji} is the fuzzy system parameter.

3.2.1. The Antecedent Network of TSFNN

The antecedent network is divided into 4 layers [34,35].

Layer A (Input layer): The number of nodes is determined by the number of inputs, which is used to convey each input variable.

Layer B (Fuzzy layer): It is used to calculate the membership degree $\mu_{A_j^i}$ of each input variable. In this study, the Gaussian membership function is adopted.

$$y = e^{-\frac{(x-c)^2}{\sigma^2}} \tag{3}$$

The parameter c and σ determine the center point of the function and the width of Gaussian membership function, respectively.

Layer C (Rule layer): It is used to calculate the firing strength α_j of every fuzzy rule. In this paper, the continuous multiplication operator is adopted.

$$\alpha_j = u_{A_1^j}(x_1) * u_{A_2^j}(x_2) \ldots * u_{A_n^j}(x_n) \tag{4}$$

where $u_{A_i^j}(x_i)$ is the corresponding subordinate function.

Layer D (Normalized layer): It is used to calculate the normalized firing strength of corresponding rules [36]. The output variable $\overline{\alpha}_j$ of the front part network is calculated by a weighted average method, which can be given by:

$$\overline{\alpha}_j = \alpha_j / \sum_{i=1}^{m} \alpha_i \tag{5}$$

3.2.2. The Consequent Network of TSFNN

The consequent network of TSFNN is divided into 3 layers, consisting of r parallel sub-networks with the same structure, each of which produces an output variable.

Layer E (Input layer): To compensate the constant in the fuzzy rule, the 0^{th} node of the input layer is $x_0 = 1$.

Layer F (Function layer): It is used to calculate the consequent parameters of every rule. Let input weight average to the unadjusted rules:

$$y_{ij} = p_{j0}^i + p_{j1}^i x_1 + \ldots + p_{jn}^i x_n \tag{6}$$

Layer G (Combined layer): It is the output layer of the entire network.

$$y_i = \sum_{j=1}^{m} \overline{\alpha}_j y_{ij} \tag{7}$$

where y_i (i = 1, 2, . . . , r) is the weighted sum of each rule. The output of the antecedent network is used as the connection weight of the layer G.

3.2.3. Network Learning Parameters

The learning parameters of TSFNN mainly include the connection weight p_{ji}^l of the consequent network and the central value c_{ij} and the width σ_{ij} of the membership functions of the nodes in layer B of the antecedent network. Suppose the error cost function as:

$$E = \frac{1}{2} \sum_{i=1}^{r} (t_i - y_i)^2 \tag{8}$$

In the formula, t_i and y_i represent the desired output and the actual output, respectively. The learning algorithm of the parameter p_{ji}^l is:

$$\frac{\partial E}{\partial p_{ji}^l} = -(t_1 - y_1)\overline{\alpha}_j x_i \tag{9}$$

$$p_{ji}^l(k+1) = p_{ji}^l(k) + \beta(t_1 - y_1)\overline{\alpha}_j x_i \tag{10}$$

By adjusting parameter p_{ji}^l, the structure of TSFNN can be simplified. The simplified structure is also a kind of multilayer feedforward network. Therefore, we refer error backpropagation algorithm of Back Propagation (BP) network into the learning algorithm to adjust parameters. The learning algorithm for parameter adjustment is as follows:

$$c_{ij}(k+1) = c_{ij}(k) - \beta\frac{\partial E}{\partial c_{ij}} \tag{11}$$

$$\sigma_{ij}(k+1) = \sigma_{ij}(k) - \beta\frac{\partial E}{\partial \sigma_{ij}} \tag{12}$$

4. Parameters of DDM

The selected parameters of DDM, namely the input and output variables of model, will directly affect the validity of the model.

4.1. Input Variables of DDM

Based on the classification of influencing factors of decision-making in the existing research [37], the ethics and legal factors are taken into account as well, and a total of 16 influencing indicators are selected to design the questionnaires according to the emergency situations evoked by red light-running behaviors. Influencing indicators are as follows: velocity of host vehicle (V_1), braking capacity of host car (B), the distance between the host vehicle and the obstacle (D), type of the right-lane vehicle (T), velocity of the right-lane vehicle (V_2), the road line shape (LS), the lane width (W), the road mark (RM), duration of red light (RL), the weather condition and the visibility (WE), type of abnormal target (AT-T), number of abnormal target (AT-N), state of abnormal target (AT-S), velocity of abnormal target (AT-V), angle before collision (θ), damage area (DA).

2000 questionnaires were distributed, 1244 were recovered and the recovery rate reached 62.2%, among which 1148 effective questionnaires were obtained, and effective recovery rate reached 92.3%. Through analyzing and processing of the questionnaire data, the input variables of the model are determined.

As for input variables, on the one hand, if the input number is less, the model is too simple to reflect the driver's decision rule precisely. On the other hand, if it is too much, the coupling relationship between the other influencing factors will increase the complexity of DDM and the training time. In this paper, principal component analysis (PCA) is adopted to convert multiple correlated indicators into fewer linear uncorrelated ones. PCA is an accepted tool in data analysis, and more generally [38]. The results of PCA for 16 influencing indicators are shown in Figure 4.

The cumulative variance contribution rate of the first five principal components reached 78.94%, indicating that components can represent the influencing factors of DDM. The further output of the rotational component matrix is shown in Table 2.

Among them, each load value is the correlation coefficient between each variable and PC. The PC with large correlation coefficients is screened; thus, the decision-making indicator set is determined, which is as shown in Table 3.

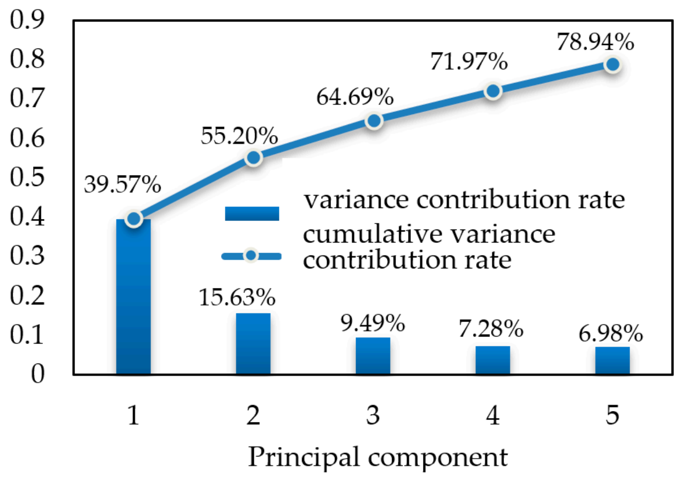

Figure 4. The results of principal component analysis (PCA) for 16 influencing indicators. The x-axis represents the first five principal components; y-axis represents the variance contribution rate of the principal component.

Table 2. Influencing factors of driving decision-making rotational component matrix.

Indicators	Components				
	1	2	3	4	5
V_1	**0.938**	−0.045	−0.088	0.022	−0.052
RL	**0.927**	−0.009	−0.027	0.209	−0.118
AT-N	**0.889**	−0.073	−0.014	0.255	0.037
W	0.787	−0.106	−0.091	0.303	−0.109
B	−0.079	0.413	0.741	−0.131	0.053
LS	0.728	−0.012	0.134	0.061	−0.112
V_2	0.699	−0.156	−0.122	0.318	0.097
AT-T	−0.129	**0.924**	0.064	−0.046	0.048
AT-S	−0.014	**0.907**	0.127	−0.054	−0.046
RM	−0.207	−0.047	**0.898**	0.250	−0.228
AT-T	−0.079	0.413	−0.131	**0.864**	0.053
DA	0.255	0.030	0.691	−0.424	0.242
T	0.511	0.001	−0.014	0.612	0.142
WE	0.491	0.096	−0.086	0.530	−0.148
D	−0.168	0.004	−0.011	0.049	**0.832**
θ	−0.191	0.032	0.105	−0017	0.593

What bold indicates higher value in a column are selected as principal components; extraction method: Main component; rotation method: with the Kaiser standard orthogonal rotation method; a. the rotation converges after 8 iterations.

Table 3. Indicator set of DDM.

Number	Indicator of Decision-Making
1	Velocity of host vehicle (V_1)
2	Duration of red light (RL)
3	Number of abnormal target (AT-N)
4	Type of abnormal target (AT-T)
5	State of abnormal target (AT-S)
6	The road marking RM
7	Velocity of the right-lane vehicle (V_2)
8	The distance between the host vehicle and the obstacle (D)

The indicator set of DDM shows that the above factors with large correlation coefficients have an important impact on driving decision-making. In the analysis of Sections 2.2 and 2.3, the indicator

AT-T and AT-N imply the ethical factors; AT-T, AT-S, RL and RM imply the legal factors. As for the indicator road mark (RM), since the emergency situations occur before the intersection stop line, each lane marking line is a solid line. Drivers cannot drive over the solid line, otherwise they will be judged as violating traffic law in China. Furthermore, there is no discrimination between the samples, thus, RM is removed. The input variables of the remaining 7 indicators of DDM are marked as X_1–X_7. Details of each input variables is shown in Table 4.

Table 4. Information of the input variable of the model.

Input Variables	Meanings of Input Variables	Principle of Process Data
X_1	Velocity of host vehicle (V_1) refers to the instantaneous speed of the experimental vehicle when the driver is making decisions.	$V_1 \in [0, 40]$, keep the data; $V_1 \in (40, \infty)$, eliminate the data.
X_2	Duration of red light (RL). $0 \leq RT \leq 3$, the right light is on just now; $RT > 3$, the right light has already been on.	$0 \leq RT \leq 3$, $X_2 = 1$; $RT > 3$, $X_2 = 2$.
X_3	Number of abnormal target (AT-N). Two groups of control experiments of AT-N = 1 and AT-N = 3 are set.	AT-N = 1, $X_3 = 1$; AT-N = 3, $X_3 = 2$.
X_4	Type of abnormal target (AT-T) is divided into pedestrians, non-motorized vehicles, pets.	AT-T = pedestrians, $X_4 = 1$; AT-T = non-motorized vehicles, $X_4 = 2$; AT-T = pets, $X_4 = 3$.
X_5	State of abnormal target (AT-S) is divided into legal and illegal behaviors. Pedestrian running, holding non-motorized vehicles, pulling pets are classified as the legal behaviors; cycling non-motorized vehicles, not pulling pets are classified as the illegal behaviors.	AT-S = legal behaviors, $X_5 = 1$; AT-S = illegal behaviors, $X_5 = 2$.
X_6.	Velocity of the right-lane vehicle (V_2) refers to the instantaneous speed of the vehicle in the right lane when the driver is making a decision.	$V_1 \in [0, 40]$, keep the data; $V_1 \in (40, \infty)$, eliminate the data.
X_7	The distance between the host vehicle and the obstacle (D) refers to the distance between the centroid of the host vehicle and the abnormal target.	It is obtainedy joint calculation of the centroid coordinate of each object in the situations, regardless of the height difference in the centroid of two vehicles.

Note: Some provinces and cities in China stipulate that motor vehicles cannot exceed the speed of 40 km/h when passing through urban road intersections.

4.2. Output Variables of DDM

The driving decision-making (D) is taken as the output variable of DDM. In the emergency situations of Section 2.1, the blue vehicle is in the middle lane, and the abnormal target bursts in front of the vehicles. In this case, the driver's decision-making is divided into the following three situations, as shown in Table 5.

Table 5. Output variables of decision-making models.

Decision-Making	Symbol	Threshold	Output Threshold Range
Braking + going straight	D_1	0.5	[0, 1]
Braking + turning left	D_2	1.5	(1, 2)
Braking + turning right	D_3	2.5	[2, 3]

D_1 refers to braking + going straight, which means that the driver drives along the current lane while braking. The abnormal target will be injured. Personnel of the host vehicle and the adjacent lane vehicles will be safe; D_2 refers to braking + turning left, which means that the driver turn left while braking. The cockpit of the host vehicle will hit the vehicle in the left lane. The personnel of the host vehicle and the left side vehicle will be injured. The vehicle in the right lane and the abnormal target will be safe; D_3 refers to the braking + turning right, which means that the driver turns right while braking, hitting the vehicle in the right lane. Personnel of vehicle in the right lane will be injured, and the host vehicle and the abnormal target will be safe. The DDM is described as shown in Figure 5.

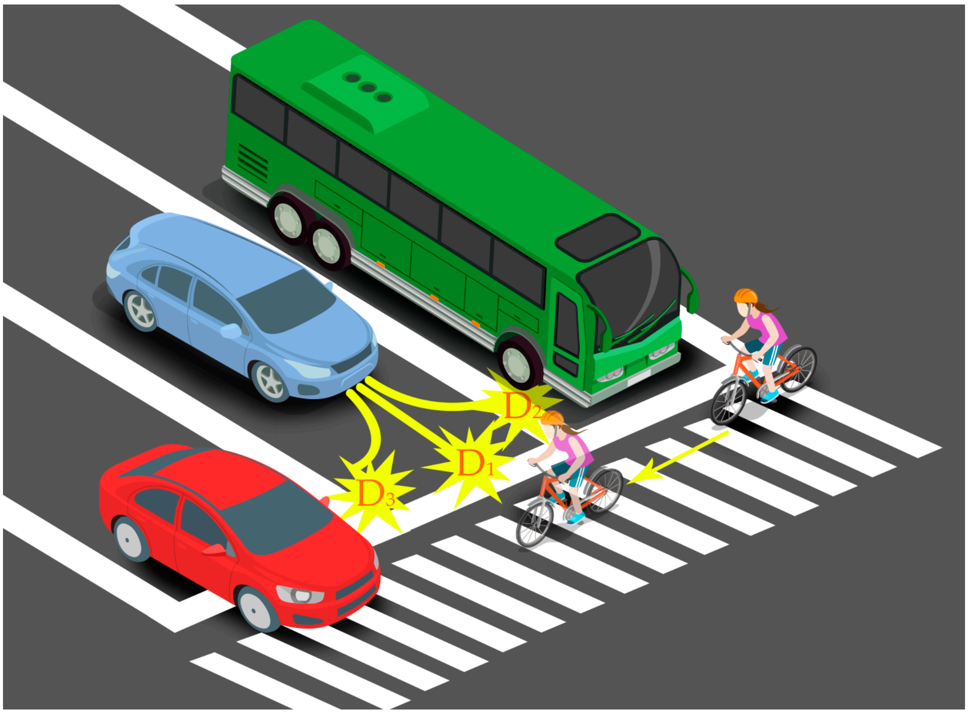

Figure 5. Three feasible driving decision-making.

5. Verification and Analysis of DDM

After establishing the model of seven input variables and one output variable, we need to use a driving simulation experiment to provide samples to train and verify DDM.

5.1. Virtual Driving Experiment

5.1.1. Scenes and Equipment of Experiment

After establishing the model of seven input variables and one output variable, we need to use a driving simulation experiment to provide samples for the model, to train and verify the factors.

UC-win/Road software is used to establish the virtual emergency situations. Virtual scene can access FORUM8.0 driving simulator which is a real vehicle control unit and the sample collection frequency is set to 20 Hz. Driving simulator can be perfectly compatible with the virtual scene to present the driver real driving experience. At the same time, the experimental equipment can synchronously output more than 80 types of parameters such as target speed and steering wheel angle in the scene. On the one hand, using the UC-win/Road data recording module, the driver's operation process is recorded, which facilitates the experimental screening. On the other hand, it has ability to output more than 80 types of recorded items to record the physical status information of the vehicle and the surrounding objects when the emergency situations occur.

Based on the ten different scenarios listed in Table 1, the input variables X_2, X_3, X_4 and X_5 are used as the basis for the division of experimental scenes. Furthermore, the dimension of X_3 is taken into account, thus, the 2 × 10 = 20 scene is set up, which corresponds to ten kinds of situations analyzed by Section 2.3. After data processing, data of input variables X_1, X_6 and X_7 can be obtained.

5.1.2. Staffs of Experiment

In the driving simulation experiment, 45 experienced drivers are recruited from those who participated in the questionnaire. Among them, there are 35 male drivers, 10 female drivers. Driving ages range from 2 to 10 years. In addition, the total driving mileage is more than 5000 km. The experimental staff are both physically and mentally healthy and energetic.

5.1.3. Process of Experiment

The volunteers firstly drive freely in the urban road network according to the traffic rules and will test after being familiar with the experimental equipment. After each scene begins, the driver drives normally. When the volunteers are about to arrive at the intersection, the control staff can control the abnormal targets and the adjacent lane vehicles, and artificially create the emergency situations. The driver makes decisions and then performs decisions until the collision with any target in face of the emergency situations, which is a set of experimental samples. In addition, each driver will participate in ten scenes. Therefore, $10 \times 45 = 450$ groups of experimental data are collected. The driving simulation experiment process is shown in Figure 6.

Figure 6. The driving simulation experiment process.

5.2. Process of Experimental Data

5.2.1. Statistics of Experimental Data

Taking AT-T as the basis for data statistics, results of DDM are shown in Figure 7.

Among the three kinds of decision-making, the number of braking + going straight is up to 258; accounting for 57.3% of the total, and the number of braking + turning right decisions is 182; accounting for 40.4%; only ten decisions are braking + turning left, accounting for 4.5%. Combined with the experimental questionnaire, the following analysis can be made:

- Most drivers believe that braking + turning left decision will have more severe consequences. Drivers drive on the right side of the road in China. Therefore, the left-turning decision will cause the cockpit to hit the abnormal target directly, which is easy to cause damage to the driver.
- When the abnormal target is pedestrian, there is no significant difference in the number of decisions making between braking + going straight and braking + turning right; as for non-motorized vehicles, braking + turning right decision slightly increased.
- When the target is a pet, in the case of uncertainty about the collision consequences of turning right, a host of drivers will choose to go straight to sacrifice pets avoiding the right side of the vehicle caused by unknown consequences.

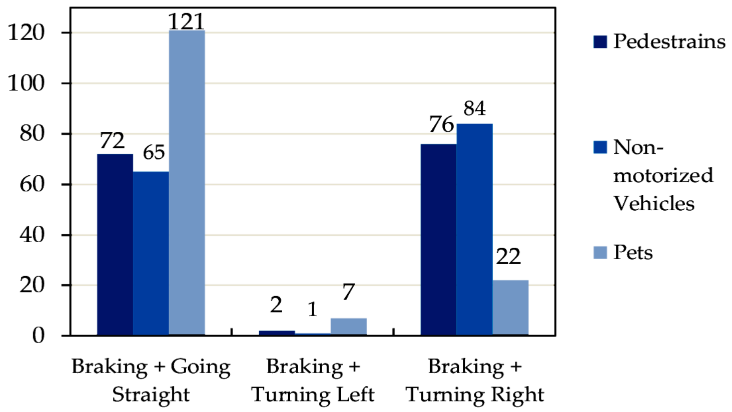

Figure 7. Statistics of experimental data.

5.2.2. Screening of Experimental Data

Human drivers may make mistakes in the execution of decision-making. Some drivers may be nervous, hesitant, and so on, leading to the results of the experiment are not consistent with the driver's real decision-making in their mind. Therefore, to solve the above problems, some unqualified experimental data need to be corrected or eliminated. The playback function of UC-win/Road 13.0 is enabled to reproduce the previous experiment process, and the volunteer can revise the previous decision to ensure that the decision is consistent with the actual operation. In addition, the volunteers also randomly select the others' experimental video to rate. A low score sample indicates that the decision is not acceptable to the public. We should eliminate such samples and improve the recognition of the total samples.

5.3. Results of Experiment

After the data processing, we eliminate 30 group data. 420 groups are used as samples for training and testing. 336 groups (80% of the total number of samples) are used as training samples (188 groups of straight samples and 148 groups of right-turning samples), and the remaining 84 groups are taken as test samples (49 groups of straight samples and 35 groups of right-turning samples) to train and verify the proposed DDM.

At the same time, back propagation neural network (BPNN) is used to establish the decision-making model for comparison. The experimental data is recorded by the data output module to train and verify DDM. BPNN is used for comparison to verify the validity of the model. With integrated system, explicit algorithmic process, data identification and simulation function, BPNN is one of most popular learning algorithms with the excellent ability to solve nonlinear problem [22,39]. To verify the performance of TSFNN, a typical feedforward BPNN is established to compare with TSFNN on the relationship between decision influencing factors and driver decision-making [22].

The training results of TSFNN and BPNN are shown in Figures 8 and 9 respectively, and the error comparison results of the two models are shown in Figure 10.

For further comparison, the mean absolute error (*MAE*) and the root-mean-square error (*RMSE*) are calculated, respectively. *MAE* can better reflect the actual situation of the forecast value error, and its calculation formula is as follows:

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|f_i - y_i| \tag{13}$$

In this formula, f_i is the predicted value y_i is the actual value and m is the sample number.

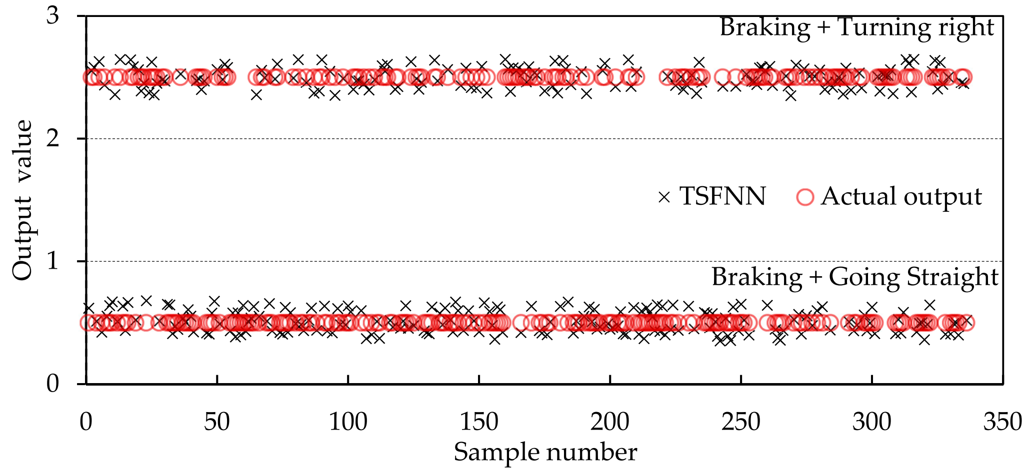

Figure 8. The training results of TSFNN.

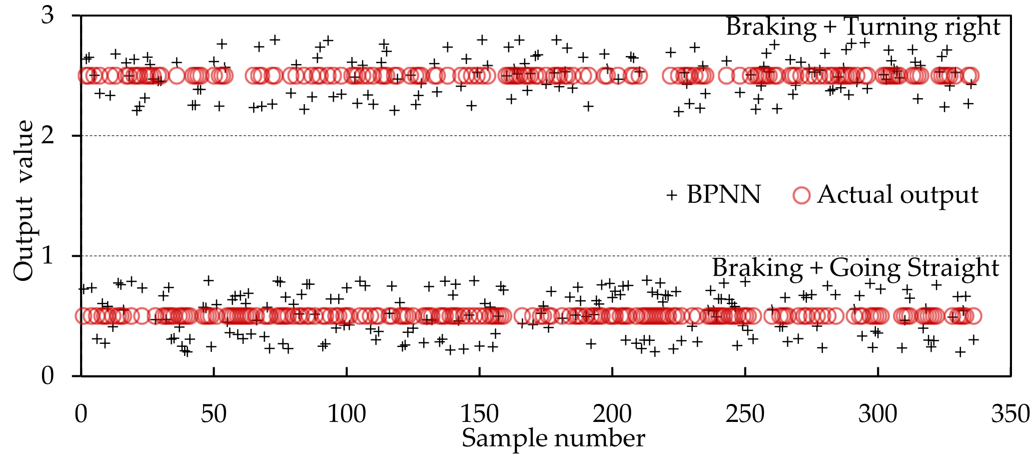

Figure 9. The training results of back propagation neural network (BPNN).

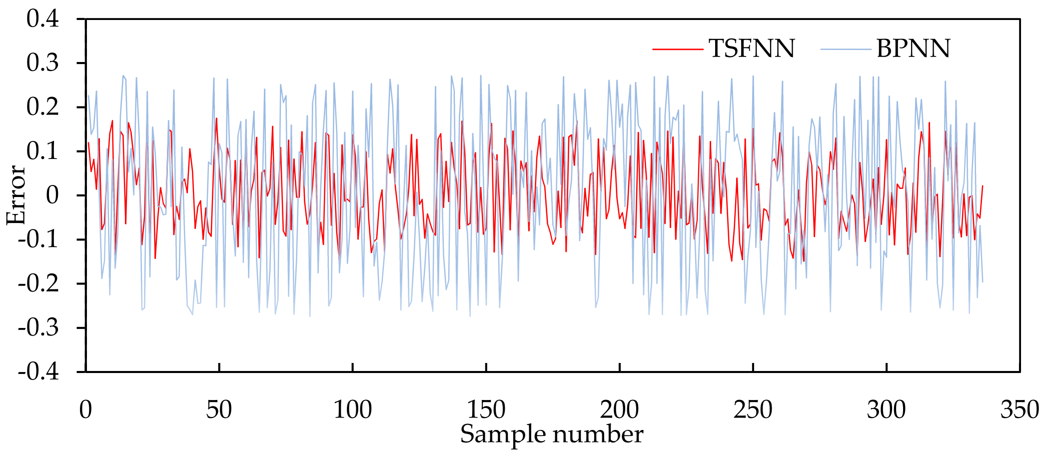

Figure 10. The error comparison results of TSFNN and BPNN.

RMSE is used to measure the deviation between the observed value and the actual value, and the formula is as follows:

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(f_i - y_i)^2} \tag{14}$$

The comparison of the two models is shown in Table 6.

The comparison results show that the decision model based on TSFNN has obvious advantages in accuracy and the overall error is smaller than BPNN. Therefore, TSFNN can accurately reflect the relationship between decision-making factors and DDM.

Table 6. Comparison of TSFNN and BPNN Prediction results.

	TSFNN				BPNN			
	Training Samples		Test Samples		Training Samples		Test Samples	
	Braking + Going Straight	Braking + Turning Right	Braking + Going Straight	Braking + Turning Right	Braking + Going Straight	Braking + Turning Right	Braking + Going Straight	Braking + Turning Right
MAE	8.08%	8.80%	7.24%	10.77%	12.11%	12.35%	11.43%	15.44%
RMSE	0.0044	0.0053	0.0037	0.0083	0.0099	0.0112	0.0092	0.0146
Maximum absolute error	17.96%	16.51%	19.60%	17.40%	27.18%	27.43%	31.18%	29.52%

6. Conclusions

In this paper, a DDM was developed to make accurate driving decision-making for AVs under the emergency situations evoked by red light-running behaviors. The ethical and legal factors which were difficult to describe in DDM were quantitatively characterized. RL, AT-T, AT-N and AT-S indicated ethical and legal factors. Seven main influencing factors of DDM were determined by PCA as the input variable of DDM. The driving decision-making (D) was developed to accomplish the inherent complex and precise tasks, including braking + going straight, braking + turning left, braking + turning right, which was taken into account as the output variable. Consequently, a DDM based on TSFNN was established. Training samples were collected by driving virtual experiments. At the same time, considering the interference of artificial factors, we eliminated the unqualified sample data. TSFNN was trained and compared with BPNN. Experimental results showed that the output results of TSFNN were more accurate, and the error was smaller than that of BPNN, and the quantitative ethical and legal factors could be accurately and successfully estimated by the proposed DDM.

Although this article integrates ethical and legal factors into DDM, there are still some limits. This paper considers the emergency condition evoked by red light-running behaviors at the intersections, but the traffic scene is infinite. We will consider more situations in the future. In addition, in the process of establishing a decision model, the correlative parameters of vehicle dynamics and the transient static decision are not considered. In addition, the influence of the dynamic space state of other objects in the situations on the driving decision is not considered either. The establishment of dynamic and real-time DDM is required in future study.

Author Contributions: S.L. and J.Z. conceived and designed the experiments; S.W. and P.L. performed the experiments and analyzed the data; P.L. and Y.L. contributed reagents/materials/analysis tools; S.L. and J.Z. wrote the paper.

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