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Evaluation on New Energy Vehicle Safety Early Warning System Based on Intelligent Optimization Algorithm

Yongan Luo[1,a], Yeheng He[1,b], Yangyong Lan[1,c]

[1]Changsha Yifeng Automotive Technology Co., Ltd., Changsha, Hunan, China
[a]18154755110@163.com, [b]544021517@qq.com, [c]1365072507@qq.com

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Abstract: With the substantial increase in the inventory of vehicles, New Energy Vehicles (NEV) have received more and more attention. At the same time, the safety of NEV has received attention. When the safety problem of NEV occurs, the communication transmission of safety warning information can be processed at the first time. Communication transmission needs to use communication technology, which is mainly used for information transmission and signal processing. However, the communication speed of the traditional new energy vehicle safety early warning system is slow, and the safety performance needs to be improved. Intelligent optimization algorithms were applied to NEV safety warning systems, and the overall structure of the NEV safety early warning system was analyzed and improved. Through testing different new energy vehicles, it was found that: applying the intelligent optimization algorithm to the safety early warning system of NEV can improve the accuracy of vehicle positioning. The intelligent optimization algorithm can improve the safety performance of NEV, and can effectively improve the communication speed of early warning information of vehicles. Vehicles with improved safety warning systems are more popular with users, and user satisfaction increased by 6.67%. The intelligent optimization algorithm has improved the safety early warning system of NEV, and the communication function of NEV has also been improved.

1. Introduction

With the rapid development of new energy automobile manufacturing industry, the safety problem of automobiles is also increasing year by year. With the rapid development of the NEV industry, many automobile manufacturers are developing their own NEV. Only by ensuring the safety of vehicles can the safety of drivers be better guaranteed. It is necessary to improve the safety warning system of new energy vehicles.

Many scholars have studied the vehicle safety early warning system. Visconti, Paolo described an innovative complete automotive control system that connects a collection device to a microcontroller board that is able to combine all the collected data to detect alarm scenarios and take alarm procedures [1]. Lee, Sang Hyeop proposed a Collision Warning System (CWS) based on individual driver driving, and finally verified the applicability of the proposed CWS through simulation [2]. Song, Wenjie introduced the real-time obstacle detection and its collision warning state classification method vehicle active safety system, through the UV parallax obstacle detection algorithm to obtain the final dynamic and relatively dynamic objects, and to classify them by comparing them with the danger area. The results proved that it can work effectively [3]. Sternlund, Simon designed lane departure warnings using the induced exposure method in order to reduce passenger car injury crashes, and compared sensitive and non-sensitive crashes in passenger cars with and without warning systems, and the analysis showed that warning systems have a positive effect in reducing lane [4]. Outay, Fatma proposed a wireless fog early warning system, in which cooperation awareness information is disseminated and used to calculate acceleration/deceleration activities. The use of the simulation framework Veins on the open source vehicle network demonstrated that this system is improving security [5]. The above research has achieved good results, but with the continuous updating of technology, there are still some problems.

Many intelligent optimization algorithms have been applied to the safety system. Lim, Wonteak proposed a hierarchical trajectory and urban autonomous driving design approach based on a combination of sampling and optimization that uses environmental models to manage complex driving environments to create a safe autonomous driving vehicle [6]. Che, Gaofeng used improved ant colony optimization algorithms to control the motion of an Autonomous Underwater Vehicle (AUV) by connecting selected nodes of the seafloor environment while avoiding collisions with complex optimal paths of the seafloor topography to ensure AUV safety [7]. Chen, Chen used the Particle Swarm Optimisation (PSO) algorithm to optimise a magnetic levitation vehicle safety system and demonstrated a closed-loop stabilisation control method for the suspension system in terms of response speed and convergence performance. A control response range based on linear matrix inequalities is defined to satisfy the optimised control performance, and the stability of the optimisation algorithm in controlling the operational variability of the vehicle is demonstrated [8]. SANA proposed a new hybrid algorithm and applied it to re-entry orbit planning for supersonic spacecraft to achieve smooth trajectories and path constrained execution with ultimate accuracy [9]. Li, Zhe developed an integrated hub motor electric vehicle model. The simulation results show that the optimized active suspension system attenuates the sensitivity of the vehicle system to electromagnetic excitation and the satisfactory balance comfort and stability between vehicle driving [10]. The above research shows that the application of intelligent optimization algorithm has a positive effect, but there are still some problems.

This paper uses the particle swarm optimization algorithm of intelligent optimization algorithm to improve the safety early warning system of new energy vehicles, and applies the PSO algorithm and Wavelet Neural Network (WNN) to the vehicle safety system, aiming to improve the safety performance of NEV and make the early warning information communication faster.

2. Application of Intelligent Optimization Algorithm in Automobile Safety Early Warning System

(1) Communication function of safe driving

The development of communication technology has a long history. In ancient times, people have mastered the traditional means of communication, such as flying pigeons, beacon fire and smoke, and post horse transmission. Nowadays, communication technology is applied in various fields, and the realization of automatic driving in automobiles cannot be separated from communication technology. Using 5G communication technology to further optimize automatic driving communication and fundamentally change the control mode of traditional vehicles can significantly improve the efficiency and safety of the traffic system, and make the interaction of vehicle network information faster and more reliable. The automatic driving technology supported by the vehicle network using 5G communication technology would enter daily life in the near future.

(2) Overall structure of new energy vehicle safety early warning system

This book establishes the safety alarm system of the system to receive vehicle transportation information and battery status information from the vehicle status terminal and the LAN bus controller. The information is provided according to the real-time data of vehicle performance. The specific method is to use the current vehicle status information obtained from the status information and the battery status information such as battery voltage, current, temperature obtained from the controller area network bus controller, and then analyze the alarm information obtained and send it to the new energy vehicle monitoring center through transmission communication. The monitoring center gives consideration to monitoring, dispatching, and receiving or executing alarms, and displays the processing results on the electronic map in real time. The monitoring center server can easily formulate the driving plan according to the alarm information, and generate instructions to issue the terminal's new energy vehicles through the network to ensure the safe operation of new energy vehicles, provide decision-making support for the operation, and achieve the goal of real-time tracking of new energy vehicles. As shown in Figure 1, the system can be divided into four parts: intelligent vehicle terminal, mobile communication system, global communication network and vehicle monitoring center.

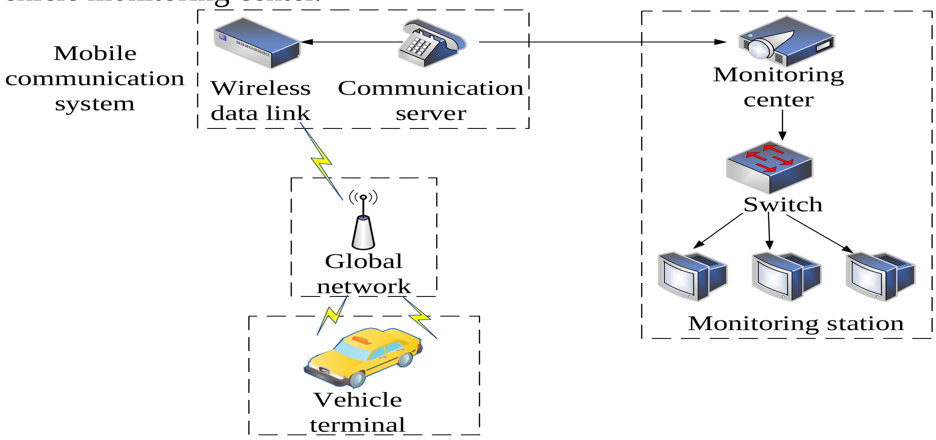

Figure 1: Overall structure of automobile safety early warning system

Among them, the intelligent vehicle terminal generates the power battery status data information, alarm type and early warning information received by the new energy vehicle through the intelligent particle swarm algorithm according to the current running state of the vehicle. It is transmitted to the monitoring center through the network, and the collected data is summarized by the server of the monitoring center to realize the monitoring, analysis and early warning of each vehicle fault information encountered.

(3) Vehicle terminal design

The structure of on-board terminal is shown in Figure 2. It includes central processing unit, communication unit, identification unit, positioning unit, human-computer interaction unit, smoke sensor, temperature sensor, humidity sensor, vibration sensor, water level sensor, transmission sensor and CAN data control circuit [11]. The central operation unit receives the data from the connection unit, and completes the preliminary judgment on the local data of new energy vehicles according to the preset alarm threshold and emergency command threshold. The circuit tester completes the connection and disconnection of the vehicle power circuit by checking the internal relay. After receiving the current vehicle status information, the user provides the user with a data interface at the on-board terminal through the ECS, connects the on-board information system and the battery management system, and receives the vehicle status data and the current data of the battery box in real time.

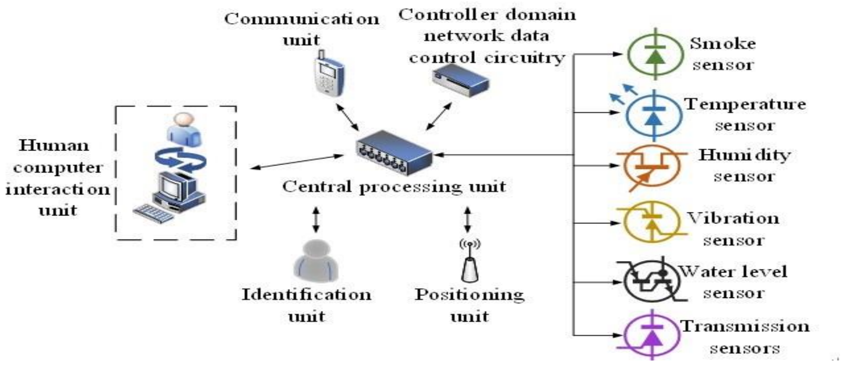

Figure 2: Vehicle terminal design

(4) Security early warning system business service

The security early warning system includes data analysis service, data access service, rescue service, early warning analysis service, maintenance planning service, battery monitoring service and other services, as shown in Figure 3. Among them, the encryption and decryption function is used to decrypt and analyze the received data, search for the nearest rescue vehicle, and guide the nearest rescue vehicle to rescue. The early warning analysis service conducts data mining and analysis on historical and current vehicle data, identifies potential anomalies of new energy vehicles and batteries, and provides solutions. The maintenance plan function analyzes the vehicle condition, battery condition, life and use mode, and develops a maintenance plan for the vehicle and battery. The battery tracking service searches, tracks and locates the lost battery in a fully controlled environment, and notifies the vehicle owner.

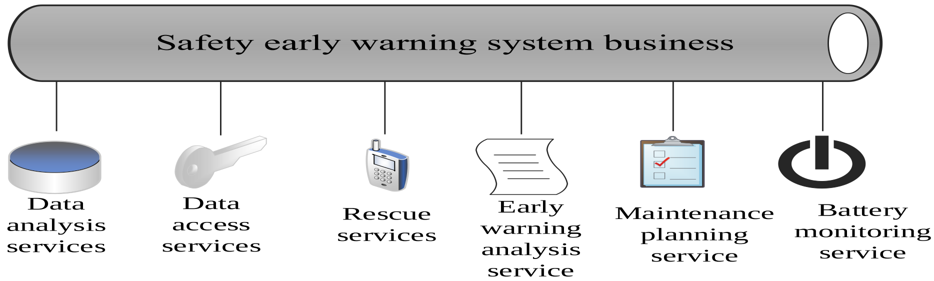

Figure 3: Business services of security early warning system

3. Intelligent Optimization Algorithm Model

(1) Wavelet neural network

As a new and rapidly developing subject in the field of mathematics, wavelet analysis not only has a profound theoretical basis, but also has extensive applications in many fields. "Wave" is a waveform in a small range with limited length and an average value of zero [12-13]. The term "small" refers to its reduction, that is, it supports the compactness of the time zone, while the so-called "wave" refers to its inconsistent positive and negative choices, that is, the form of amplitude oscillation.

Definition: If $\psi(t) \in L^2(R)$ and the conditions are met:

$$C_\psi = \int_{-\infty}^{+\infty} \frac{|\hat{\psi}(\omega)|}{|\omega|} d\omega < +\infty \tag{1}$$

Among them, ψ is called "parent wavelet" or "base wavelet", Fourier transform of ψ is $\hat{\psi}$, and Formula 1 is called receiving state. The wave function generated by ψ can be expressed as:

$$\psi_{p,q}(t) = \frac{1}{\sqrt{|p|}}\psi(\frac{t-q}{p}), p,q \in R, p \neq 0 \tag{2}$$

Among them, p is the scaling parameter and q is the mediation parameter. According to the wavelet theory, in order to make the discrete wavelet function of $\{\psi_{a,b}(t)\}$ meet the process conditions in $L^2(R)$, it is necessary to select the appropriate expansion coefficient and translation coefficient. For any function $f(\cdot) \in L^2(R)$, it is multiplied by wavelet expansion $C_{p,q}$. Corresponding to wavelet function $\psi_{p,q}$, function $f(\cdot)$ can be approximated with arbitrary accuracy:

$$\hat{f}_i(t) = \sum_{p,q} C_{p,q}\psi_{p,q}(t) \tag{3}$$

(2) Structure of WNN

The WNN would express the signal through the transition and scaling transformation of the nonlinear wavelet basis function [14]. The wavelet function has obvious advantages in selecting the excitation function of neural network, which is helpful to improve the approximation effect of the function.

Principle of discrete wavelet transform: a base wavelet $\psi(m_{t-1}, m_{t-1},..., m_{t-a})$ is selected in Hilbert space to meet the admissibility condition [15]:

$$c_\psi = \int_{L^2} \frac{\left|\hat{\psi}(\omega_{m_{t-1}}, \omega_{m_{t-2}},..., \omega_{m_{t-a}})\right|}{\left|\omega_{m_{t-1}}\right|^2 + \left|\omega_{m_{t-2}}\right|^2 + ... + \left|\omega_{m_{t-a}}\right|^2} d\omega_{m_{t-1}},..., d\omega_{m-a} < +\infty \tag{4}$$

Among them, $\hat{\psi}(\omega_{m_{t-1}}, \omega_{m_{t-2}},..., \omega_{m_{t-a}})$ is the Fourier transform of $\psi(\omega_{m_{t-1}}, \omega_{m_{t-2}},..., \omega_{m_{t-a}})$.

Function $\psi(\omega_{m_{t-1}}, \omega_{m_{t-2}},..., \omega_{m_{t-a}})$ is superposed with scaling, translation and rotation factors to obtain wavelet basis function:

$$\psi_{p,\theta,\bar{q}}(m_{t-1},..., m_{t-a}) = p^{-1}\psi(p^{-1}r_{-\theta}(m_{t-1} - q_{m_{t-1}},..., m_{t-a} - q_{m_{t-a}})) \tag{5}$$

Among them, p is the scale factor and $q = (q_{m_{t-1}},..., q_{m_{t-a}}) \in R^a$ is the average factor. $r_{-\theta} = (m_{t-1},...m_{t-a})$ is the rotation factor, and $r_{-\theta}$ is defined as:

$$r_{-\theta} = (m_{t-1},..., m_{t-i},..., m_{t-j},...., m_{t-a}) = m_{t-i}\cos\theta - m_{t-j}\sin\theta, 1 \le i \le j \le a \tag{6}$$

If function $\psi_{p,\theta,\bar{q}}(\cdot)$ can meet the space frame attribute $P\|f\|^2 \le \sum_{p,q}\left|<\psi_{p,\theta,\bar{q}}(\cdot)>\right|^2 \le Q\|f\|^2$, people need to select appropriate translation and extension parameters $p > 0, q, \theta$.

The form of wavelet neural network approximation B is:

$$\hat{f}(\cdot) = \sum_{i=1}^{y} \omega_i \psi_{p,\theta,\bar{q}}(m_{t-1}, m_{t-2},..., m_{t-a}) \tag{7}$$

It can also be written as:

$$\hat{f}(\cdot)=\sum_{i=1}^{y}\omega_i\psi_i(\cdot) \tag{8}$$

(3) Wavelet neural network fusion algorithm for PSO

PSO algorithm is a simulation of natural and social systems. A collective with some interaction can be defined as a group. Compared with the simple behavior of individuals in the group, the behavior of the whole group is very complex. The simple combination of individuals constitutes a cluster. The interaction between communities, individuals and the environment is called "swarm intelligence".

For most global optimization problems, particle swarm optimization can be used as a solution. When PSO first processes a large amount of data in the form of a database, its maximum distribution and parallelism can ensure the processing technology [16-17]. In the initial stage of PSO, particle swarm is randomly generated, and the initial velocity and position of each particle are also randomly generated. Then, the velocity and position of particles would be updated and repeated according to Formula 1 and Formula 2 until a satisfactory solution is found.

$$v_{id}=WV_{id}+c_1r_1(p_{id}-m_{id})+c_2r_2(p_{gd}-m_{id}) \tag{9}$$

$$m_{id}=m_{id}+v_{id} \tag{10}$$

Among them, v_{id} is the velocity of the particle, m_{id} is the position of the particle, and p_{id} is the ideal state of the particle itself, that is, the ideal environment. p_{gd} represents the best position of the whole group, that is, the global best.

With regard to statistical methods, the optimal method and search process of genetic algorithm do not require reconstruction information such as gradient information, but only the fitness function and objective function that affect the search direction.

$$m_i^{t+1}=p_cm_i^t+(1-p_c)m_j^t \tag{11}$$

$$m_j^{t+1}=p_cm_j^t+(1-p_c)m_i^t \tag{12}$$

The inertia weight factor is introduced into the particle swarm optimization algorithm:

$$w(k+1)=(w\_init-w\_end)*(k\_\max-k)/k\_\max+w\_end \tag{13}$$

(4) Establishment of alarm system model

The system takes six state variables $M=[m_1,m_2,m_3,m_4,m_5,m_6]^T$ through the positioning unit. Among these information, longitude, latitude, speed, direction and time information are obtained from the recommended location information format of the location, and altitude information is obtained from the fixed location data presentation format [18-19]. These six state variables are used as the input of the neural network. The wavelet basis function of the WNN is the Morlet function, and the output terminal generates four state variables $Y=[y_1,y_2,y_3,y_4]^T$. Among them, y_1 represents local alarm, y_2 represents regional alarm, y_3 represents line deviation alarm, and y_4 represents overspeed alarm.

Setting the number of neurons in the hidden layer is also a key step to determine the overall structure of the network. The more neurons in the hidden layer, the more search space of the algorithm can be expanded, which is conducive to good classification and projection of nonlinear information, and is very beneficial to wavelet network integration [20]. The number of hidden layer nodes is set to 3. The basic wavelet function selects the most common Morlet wavelet, whose function expression is:

$$f(m) = \cos(1.75m)e^{-m^2/2} \tag{14}$$

The structure of WNN is shown in Figure 4.

In the figure, m_1 represents the input terminal, m_2 represents the latitude, m_3 represents the altitude, m_4 represents the relative speed, m_5 represents the heading to the ground, and m_6 represents the time.

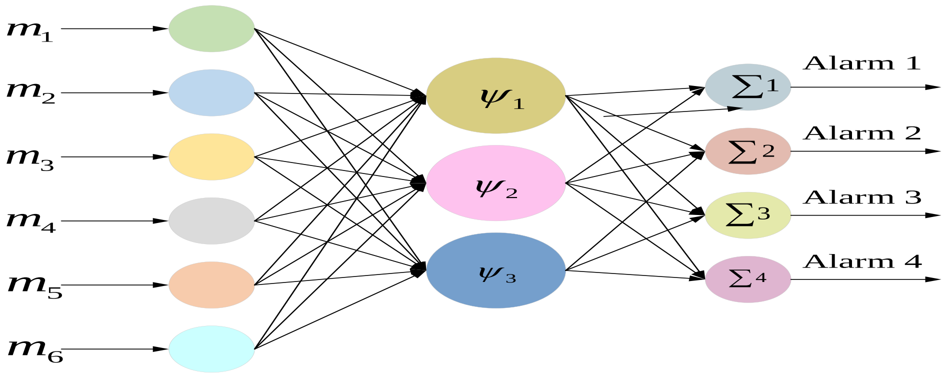

Figure 4: Structure of a wavelet neural network

4. Impact of Intelligent Optimization Algorithm on Safety Early Warning System

The safety early warning system of new energy vehicles is very important. This paper uses PSO algorithm of intelligent optimization algorithm to improve the safety early warning system of vehicles, and tests the impact of intelligent optimization algorithm on the safety early warning system. The following experiment is designed: two new energy vehicles of the same type are selected for testing. Among them, vehicle A is a traditional safety warning system and vehicle B is a safety warning system optimized by using intelligent optimization algorithms. It conducts vehicle positioning accuracy test, safety performance test, early warning information communication time test and user satisfaction test on the safety early warning system of two new energy vehicles. The test results of different safety early warning systems and the impact of intelligent optimization algorithms on the safety early warning system of new energy vehicles are observed, and the experimental results are recorded and analyzed [21-22].

(1) Automobile positioning accuracy test

When the car breaks down while driving, the car is located at the first time, and can be rescued in time to ensure the safety of drivers. The accuracy of two new energy vehicles shall be positioned and tested on the same route. The vehicle positioning accuracy is tested when the distance is 100 m, 500 m 1000 m, 5000 m and 10000 m. The test results of two vehicles are observed, recorded and analyzed, and the results are shown in Figure 5.

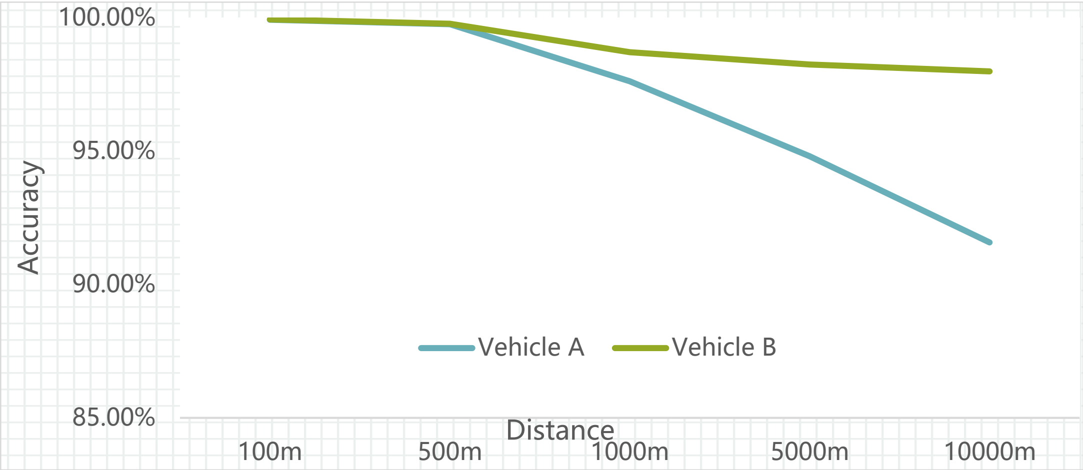

Figure 5: Automobile positioning accuracy test

It can be seen from Figure 5 that with the increasing distance, the accuracy of vehicle positioning is also declining. The decline speed of vehicle A positioning accuracy using the traditional safety early warning system is fast, while the decline speed of vehicle B using the intelligent optimization algorithm safety early warning system is slow. When the distance is 100 meters, the positioning accuracy of the two vehicles is similar, 99.92% for vehicle A and 99.93% for vehicle B. When the distance is 500, there is no significant difference in the positioning accuracy between the two vehicles, vehicle A is 99.75%, and vehicle B is 99.77%. When the distance is 1000 meters, the positioning accuracy of the two vehicles starts to differ, with vehicle A accounting for 97.61% and vehicle B accounting for 98.7%. When the distance is 5000 meters, the difference of positioning accuracy between the two vehicles increases, vehicle A is 94.80%, and vehicle B is 98.24%. When the distance is 1000m, the positioning accuracy of the two vehicles differs greatly, vehicle A is 91.57%, and vehicle B is 97.98%.

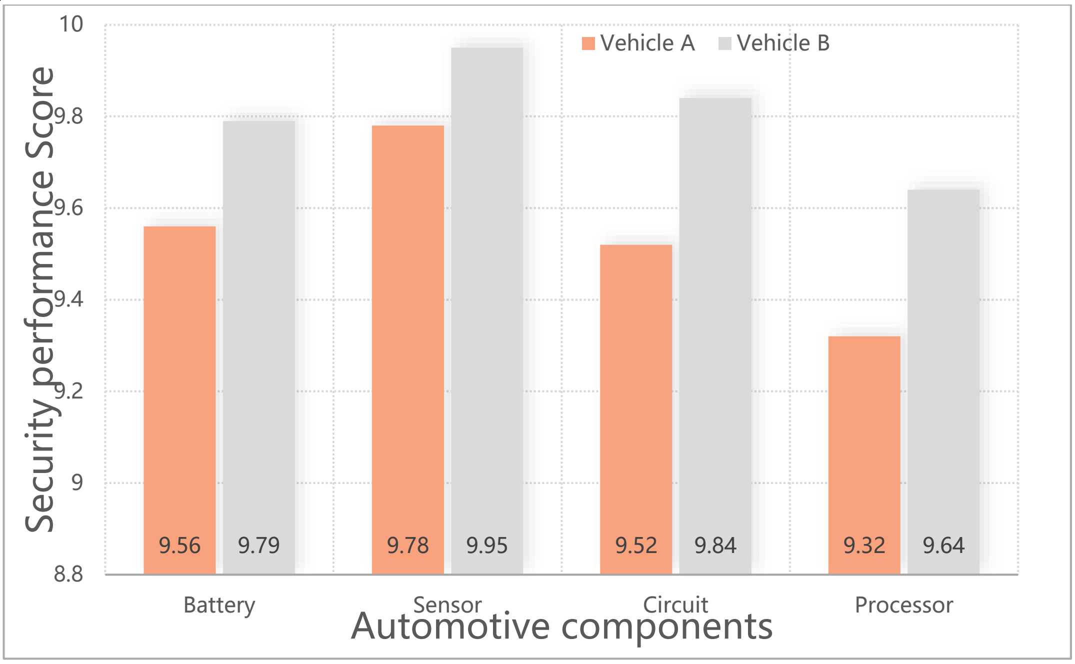

Figure 6: Security performance test

(2) Safety performance test

The safety performance of NEV is related to the health and safety of drivers themselves. The safety performance test is conducted on two vehicles, and the safety performance scores are made on the battery safety performance, sensor safety performance, circuit safety performance and processor safety performance of new energy vehicles. The safety performance test results of the two vehicles are observed, recorded and analyzed, and the results are shown in Figure 6.

It can be seen from Figure 6 that the security performance test scores of different components are different. Among them, the security performance of the sensor is higher and the security performance of the processor is lower. The battery safety performance of vehicle A is 9.56, and that of vehicle B is 9.79. The battery safety performance of vehicle B is 0.23 higher than that of vehicle A. The sensor safety performance of vehicle A is 9.78, and that of vehicle B is 9.95. The sensor safety performance of vehicle B is 0.17 higher than that of vehicle A. The circuit safety performance of vehicle A is 9.52, and that of vehicle B is 9.84. The circuit safety performance of vehicle B is 0.32 higher than that of vehicle A. The processor safety performance of vehicle A is 9.32, and that of vehicle B is 9.64. The processor safety performance of vehicle B is 0.32 higher than that of vehicle A. To sum up, the vehicle safety performance of the safety early warning system using intelligent optimization algorithm is higher than that of the traditional safety early warning system, and the intelligent optimization algorithm can improve the safety performance of new energy vehicles.

(3) Early warning information communication speed test

In case of problems with new energy vehicles, the vehicle safety early warning system would return the early warning information. The faster the communication speed is, the faster the early warning information would be processed, and the more safe the new energy vehicles would be. The early warning information communication speed of two vehicles is tested. Five obstacles are set in front of the vehicle, and the return time of the early warning information of no obstacles is recorded. The difference between the test results of two new energy vehicles is observed, and the results are recorded and analyzed, as shown in Figure 7.

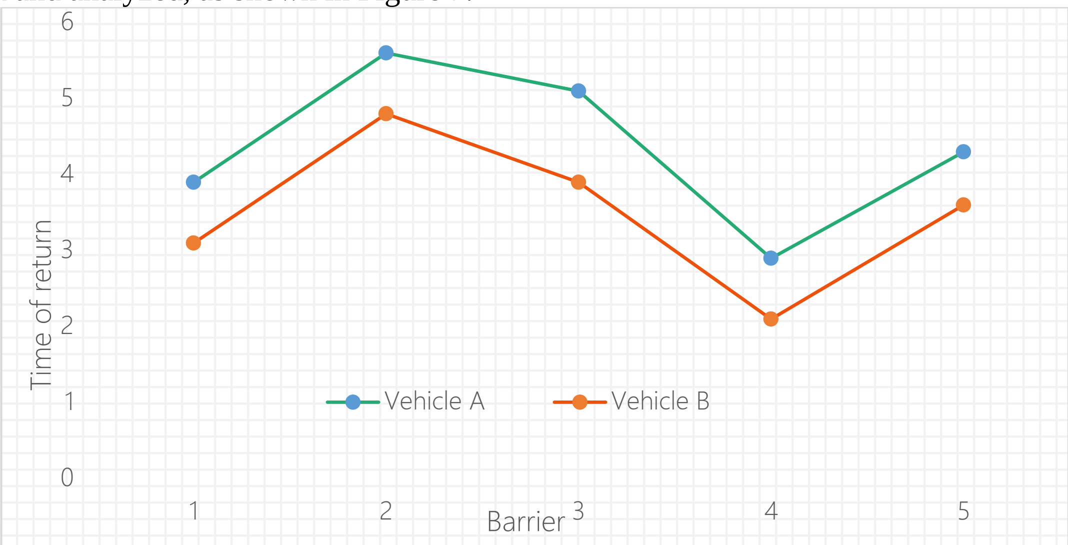

Figure 7: Early warning information communication speed test

It can be seen from Figure 7 that the return time of early warning information of vehicle B is lower than that of vehicle A. The shorter the return time, the faster the communication speed of early warning information. Among them, when encountering the first obstacle, the return time of early warning information of vehicle A is 3.9 seconds, and that of vehicle B is 3.1 seconds. The communication speed of early warning information of vehicle B is 0.8 seconds faster than that of vehicle A. When encountering the second obstacle, the return time of early warning information of vehicle A is 5.6 seconds, and that of vehicle B is 4.8 seconds. The early warning information communication speed of vehicle B is 0.8 seconds faster than that of vehicle A. When encountering the third obstacle, the return time of early warning information of vehicle A is 5.1 seconds, and that of vehicle B is 3.9 seconds. The communication speed of early warning information of vehicle B is 1.2 seconds faster than that of vehicle A. When encountering the fourth obstacle, the return time of early warning information of vehicle A is 2.9 seconds, and that of vehicle B is 2.1 seconds. The communication speed of early warning information of vehicle B is 0.8 seconds faster than that of vehicle A. When encountering the fifth obstacle, the return time of early warning information of vehicle A is 4.3 seconds, and that of vehicle B is 3.6 seconds. The communication speed of early warning information of vehicle B is 0.7 seconds faster than that of vehicle A. To sum up, the application of intelligent optimization algorithm to the safety early warning system of NEV can effectively improve the communication speed of early warning information of vehicles.

(4) User satisfaction test

Ten users were randomly selected to score the satisfaction of two vehicles. Among them, the first five users scored the satisfaction of vehicle A, and the last five users scored the satisfaction of vehicle B, recording and analyzing the satisfaction scores of 10 users. The specific data of 10 users are shown in Table 1, and the user satisfaction rating results are shown in Figure 8.

Table 1: User specific data sheet

vehicle	User	Gender	Gge	Driving age
Vehicle A	1	male	38	15 years
	2	male	39	17 years
	3	male	38	18 years
	4	male	40	17 years
	5	male	36	15 years
Vehicle B	1	male	38	14 years
	2	male	35	17 years
	3	male	34	13 years
	4	male	35	15 years
	5	male	38	17 years

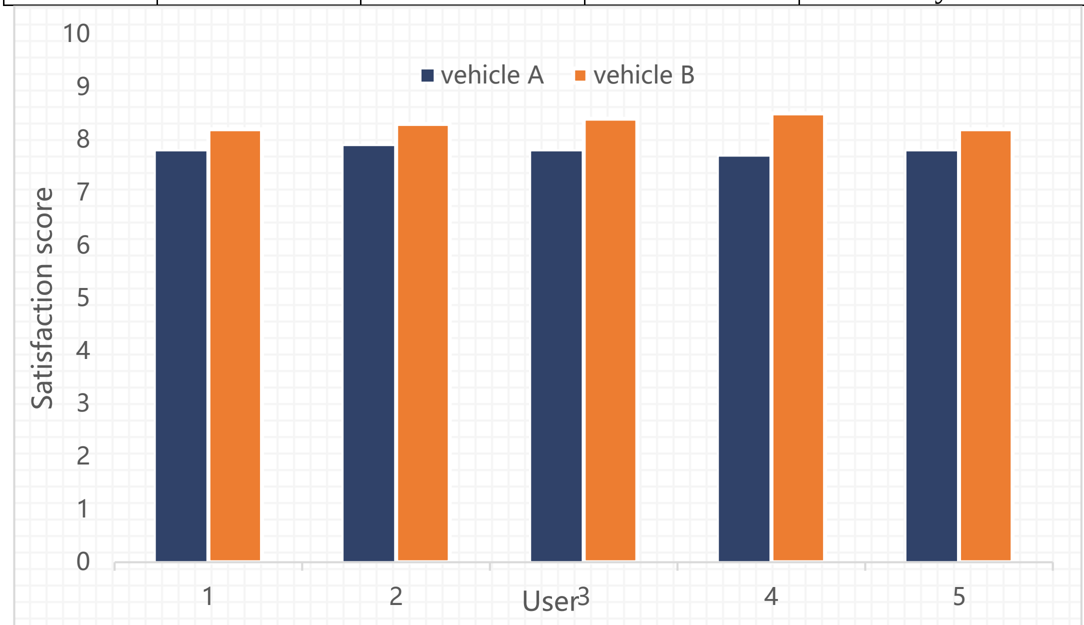

Figure 8: User satisfaction score results

It can be seen from Figure 8 that the user satisfaction score of vehicle B is significantly higher than that of vehicle A. The customer satisfaction score of vehicle A is between 7.5 and 8.0, and that of vehicle B is between 8.0 and 8.5. The average satisfaction score of new energy vehicle A is 7.8, and the average satisfaction score of new energy vehicle B is 8.32. To sum up, vehicle B using intelligent optimization algorithm to improve the safety early warning system is more popular with users, and the user satisfaction score has increased by 6.67%.

5. Conclusions

Compared with cars, NEV are more environmentally friendly. As a result, NEV safety problems also emerge in endlessly. This paper improved the safety early warning system of new energy vehicles to ensure that vehicles can communicate when encountering safety problems, and the early warning information can be returned in a timely manner. Through the experiment, it was found that the application of intelligent optimization algorithm to the safety early warning system of NEV can improve the communication speed of safety early warning information, more accurately locate NEV, and make contributions to the development of NEV.

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