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Variation of New Energy Vehicle Product Scores Based on Fuzzy Rough Set Theory and Cellular Automaton

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Abstract: - This study investigates the fluctuation in product scores of new energy vehicles (NEVs) using a combination of fuzzy rough set theory and cellular automaton. By integrating these two methodologies, we aim to provide a comprehensive understanding of how NEV product scores evolve over time. Firstly, the fuzzy rough set theory is employed to handle the uncertainty and imprecision inherent in NEV product evaluation, optimizing the selection of influential factors. Subsequently, a cellular automaton model is utilized to simulate the dynamic changes in NEV product scores, incorporating factors identified through fuzzy rough set theory. Through this combined approach, we can continuously monitor and analyze the variations in NEV product scores, enabling stakeholders to make informed decisions for improving product competitiveness and market performance. This study contributes to the advancement of methodologies for evaluating NEV products and offers insights into the dynamic nature of their competitive landscape.

Keywords: Fuzzy Rough Set Theory; Cellular Automaton; New Energy Vehicles; Product Score Variation.

I. INTRODUCTION

The development of NEVs not only contributes to promoting the transformation and upgrading of China's automotive industry but also facilitates the shift from traditional fuel vehicles to more environmentally friendly and efficient energy forms, thus fostering technological innovation and industrial upgrading. Consequently, the development of NEVs not only enhances the international competitiveness of China's automotive industry but also represents a crucial approach to achieving sustainable development in the automotive sector.

To better develop the NEV industry, it is essential not only to have top-level planning and design at the national level but also for individual enterprises to constantly understand the competitiveness of their own products. There are numerous factors influencing NEV products. To accurately understand the importance of different indicators affecting NEV products, this paper introduces the fuzzy rough set theory, which helps identify and select the most important attributes or indicators by analyzing dependencies and correlations within the data. This theory, with its strong practicality, has been successfully applied in various fields.

After constructing the attribute set of NEV influencing factors, it is necessary to continuously calculate the product score of NEVs. This score mainly relies on the average score of numerous sample data, with each data point's indicators sourced from the attribute set. As the sample data comes from the neighboring states of the sample, it belongs to a discrete system in both time and space. To address this, cellular automata (CA) are introduced. CA is a method used to simulate local rules and connections and has been widely applied in various fields such as social, economic, military, and scientific research.

Given the characteristics of the influencing factors of NEV product competitiveness and the advantages of fuzzy rough set theory and cellular automata, this paper proposes a study on "Variation of New Energy Vehicle Product Scores Based on Fuzzy Rough Set Theory and Cellular Automaton." The aim is to provide a method for real-time calculation of NEV product competitiveness scores, thus promoting the rapid development of the NEV industry.

II. THE MODEL AND METHODOLOGY

The research methodology of this paper follows the steps of constructing the indicator set of factors influencing the competitiveness of new energy vehicle (NEV) products, optimizing indicators and calculating weights using rough set theory, initializing cellular automata, simulating and analyzing cellular automata, results, and analysis. Among these steps, optimizing indicators and calculating weights using rough set theory, and simulating and analyzing cellular automata are the two most crucial steps, which directly impact the final results and analysis. Each step will be elaborated on in detail later. Figure 1 presents the research framework and

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roadmap of this paper.

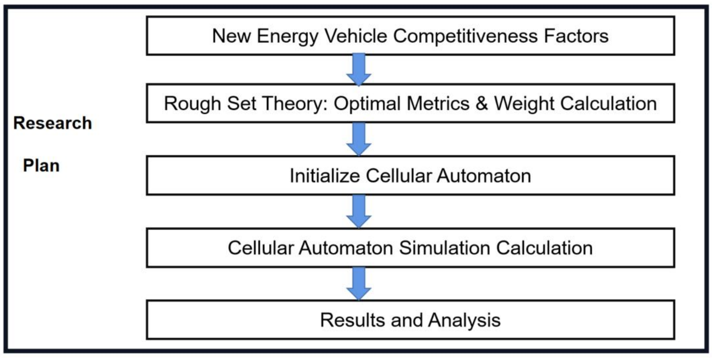

Figure 1. Research Framework and Roadmap

A. Construction of Indicators for New Energy Vehicle Product Competitiveness

The authors of this paper have concluded, through calculations based on internet big data and the review of relevant theoretical papers, that the indicators influencing the competitiveness of new energy vehicle (NEV) products include eight initial indicators: price, driving range, charging convenience, policies, subsidies, level of intelligence, technological innovation (technological level), and safety performance. Figure 2 illustrates the set of indicators for the competitiveness of NEV products.

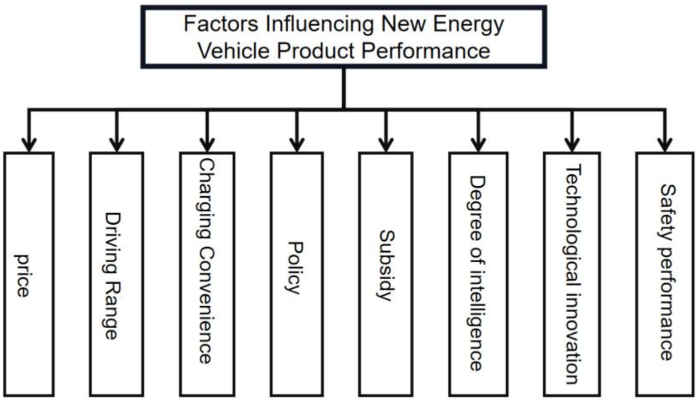

Figure 2. Set of Indicators for New Energy Vehicle Product Competitiveness

1) Indicator Analysis

(1) Price. The selling price of NEVs is generally higher than that of traditional fuel vehicles due to higher costs in technological development, material selection, and battery manufacturing. Therefore, price is a key factor directly affecting the brand competitiveness of NEVs.

(2) Driving Range. A short driving range may pose frequent risks of battery depletion to consumers during long-distance travel or inter-city trips, leading to inconvenience and anxiety. Conversely, NEVs with longer driving ranges can alleviate such concerns, allowing consumers to use them with greater confidence. Therefore, driving range is a primary factor directly influencing the brand competitiveness of NEVs.

(3) Charging Convenience. If charging facilities are widely distributed and cover the main areas of consumers' daily travel, consumers are more inclined to purchase NEVs. This implies that they can conveniently find charging stations when needed, ensuring the continuity and convenience of their travels. Conversely, scarce or unevenly distributed charging facilities may cause consumers to hesitate in purchasing NEVs due to concerns about charging issues. Charging convenience is a key factor influencing consumer purchasing decisions.

(4) Policy and Subsidy. Government subsidy policies can directly reduce the cost of purchasing NEVs for consumers. By providing subsidies for vehicle purchases, reducing or exempting vehicle purchase taxes, and offering preferential car loan rates, the government can significantly alleviate the financial burden on consumers, making NEVs more competitive in terms of price compared to traditional fuel vehicles. This economic incentive is one of the important factors driving consumers to choose NEVs.

(5) Level of Intelligence. Intelligent technology also enhances the energy utilization efficiency of NEVs. By precisely controlling the vehicle's powertrain system, battery management system, etc., NEVs can better utilize energy, increase driving range, and reduce energy consumption. This is undoubtedly an important attraction for

environmentally conscious and energy-saving consumers.

(6) Technological Innovation. Technological innovation enriches the functionality and experience of NEVs. With the development of intelligent and connected technologies, NEVs are no longer just transportation tools but also intelligent mobile terminals. Consumers can enjoy more convenient and intelligent travel experiences through features such as remote control, voice interaction, and real-time navigation provided by the onboard systems. This innovative functional experience increases the attractiveness of NEVs and encourages more consumers to purchase them.

(7) Safety Performance. Consumers are concerned about the active safety performance of NEVs, including various safety assistance systems such as automatic emergency braking, blind spot monitoring, lane departure warning, etc. These systems can provide additional safety assurances at critical moments, reducing the likelihood of accidents. Consumers typically prefer models that score high in safety tests or have more safety features. Taking all these factors into account, this paper proposes that price, driving range, charging convenience, policies, subsidies, level of intelligence, technological innovation (technological level), and safety performance are important factors influencing the brand competitiveness of NEVs.

2) Definition of Indicator Data

The data formats, sizes, etc., for each indicator as shown in Table 1 are provided below. Subsequently, suitable data preprocessing methods will be selected based on the different data types. Table 1 presents the interpretation of the indicator.

Table 1. Interpretation of Indicator Data

Index	Indicator Name	Data Format	Data Size	Description
1	Price	Continuous	100,000 - 300,000	Selling price of new energy vehicles
2	Driving Range	Continuous	≤600KM	Average driving range of various new energy vehicle models
3	Charging Convenience	Discrete	Yes/No	Presence of charging station/charging convenience
4	Policy	Continuous	Units/Tens	Number of new energy vehicle-related policies released
5	Subsidy	Continuous	Thousands/Tens of thousands	Based on different vehicle models and subsidy policies
6	Level of Intelligence	Discrete	L2, L3, L4	Determined based on different vehicle models
7	Technological Innovation	Discrete	High/Medium/Low	Classified based on enterprise technological innovation level
8	Safety Performance	Continuous	Units/Tens	Number of safety configurations

B. The rough set theory optimization indicators and calculation weights

1) Rough Set Method

The rough set theory method mainly consists of four parts: data standardization, data discretization, indicator (attribute) reduction, and indicator weighting. Among them, the most important part is data discretization, which is the research object of the rough set theory method and the basis for forming a new indicator system. Figure 3 depicts the research roadmap of the rough set theory method.

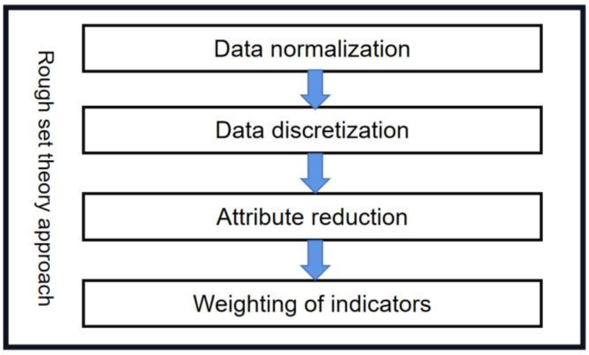

Figure 3. Steps of Evaluation Model Based on Rough Set

In this paper, it is assumed that the index of the evaluation objects (sample data's identifier) is denoted as $U=\{u_1,u_2,\cdots,u_m\}$, and the evaluation criteria (conditional attributes) are denoted as $C=\{c_1,c_2,\cdots,c_n\}$. As indicated in Figure 2, n = 9, and the evaluation data of the evaluation objects ui under the criteria cj are represented as Xi,j. Therefore, the evaluation matrix of evaluation object U under evaluation criteria C is denoted as X, as shown in the following formula (1).

$$X=\begin{bmatrix} x_{1,1},x_{1,2},\cdots,x_{1,n} \\ x_{2,1},x_{2,2},\cdots,x_{2,n} \\ \vdots \quad \vdots \quad \vdots \\ x_{m,1},x_{m,2},\cdots,x_{m,n} \end{bmatrix} \tag{1}$$

Data Standardization

The indicators in Figure 2 involve different dimensions. To ensure the accuracy of data calculation in subsequent sections, this paper does not directly discretize the data on the original scale. Instead, it standardizes continuous data using the standardization method. Different indicators with different meanings are standardized differently:

For indicators where larger values indicate superiority, the calculation method is as follows (Formula (2))[5]:

$$r_{i,j}=\frac{x_{i,j}-\min(x_j)}{\max(x_j)-\min(x_j)},i=1,\cdots,n,j=1,\cdots,m \tag{2}$$

For indicators where smaller values indicate superiority, the calculation method is as follows (Formula (3))[6]:

$$r_{i,j}=\frac{\max(x_j)-x_{i,j}}{\max(x_j)-\min(x_j)},i=1,\cdots,n,j=1,\cdots,m \tag{3}$$

Therefore, the standardized evaluation matrix can be obtained as follows:

$$R^*=\begin{bmatrix} r^*_{1,1},r^*_{1,2},\cdots,r^*_{1,n} \\ r^*_{2,1},r^*_{2,2},\cdots,r^*_{2,n} \\ \vdots \quad \vdots \quad \vdots \\ r^*_{m,1},r^*_{m,2},\cdots,r^*_{m,n} \end{bmatrix} \tag{4}$$

2) Data Discretization

Data discretization refers to partitioning the value range of continuous attributes into several discrete intervals, and finally representing the attribute values falling in each sub-interval with different integer values [7].

The main purpose of data discretization is to convert continuous data into categorical variables for better statistical analysis and model building. It can reduce data complexity, remove noise and outliers, improve data mining efficiency and accuracy, reduce storage space and computation time, and facilitate data calculation and statistical analysis modeling in subsequent sections.

(1) For continuous price data, the data discretization scheme is given by Formula (5).

$$p=round(\frac{min\_p}{10000}) \tag{5}$$

Where, min_p represents the minimum price band, round is the rounding function, and p denotes the discretized price.

(2) For continuous driving range data, the data discretization scheme is given by Formula (6).

$$d\_r^*=round(\frac{d\_r}{100}) \tag{6}$$

Where, d_r represents the minimum range band, round is the rounding function, and d_r* denotes the discretized minimum range.

(3) For continuous subsidy data, the data discretization scheme is given by Formula (7).

$$subsidy^*=round(\frac{subsidy}{1000}) \tag{7}$$

Where, subsidy represents the subsidy amount, round is the rounding function, and subsidy* denotes the discretized subsidy amount.

(4) For continuous policy data, since the size of policy data corresponds directly to the number of policies, it can be considered as inherently discrete data. Therefore, there is no need to perform conversion in this paper.

3) Indicator (Attribute) Reduction

Suppose the data group C forms an attribute set, and if attribute a belongs to C, if $ind(C) = ind(C - \{a\})$, then attribute a is referred to as a multiple attribute of the attribute set C, or it is called an attribute of C that can be omitted; otherwise, it is referred to as a single attribute of C, or it is called an attribute of C that cannot be omitted [8-10].

If every attribute $a_i^* \in C$ is a single attribute of C, then the attribute set C is considered to be mutually independent, and there are no relationships between the attributes. C forms an independent information system. Conversely, if C contains multiple attributes, redundant attributes a_i^* can be removed, resulting in a simplified attribute set C'. The steps for indicator (attribute) reduction are as follows:

(1) Suppose there is an attribute set C. The data of C is shown in Table 2.

Table 2. Data table of attribute set C.

U	a	b	c	U	a	b	c
x_1	0	0	0	x_5	0	0	0
x_2	1	0	0	x_6	0	1	1
x_3	1	2	2	x_7	2	1	2
x_4	0	1	1	x_8	2	2	3

Here, the attribute set $U = \{x_1, x_2, \cdots, x_8\}$, conditional attributes $C = \{a, b, c\}$, U / c_i represent the classification of the attribute set U based on the values of the attributes c_i. The overall system classification results are as follows.

(2) Classifying the attribute set U based on single attributes yields the following conclusions.

$$U / a = \{\{x_1, x_4, x_5, x_6\}, \{x_2, x_3\}, \{x_7, x_8\}\}$$

$$U / b = \{\{x_1, x_2, x_5\}, \{x_4, x_6, x_7\}, \{x_3, x_8\}\}$$

$$U / c = \{\{x_1, x_2, x_5\}, \{x_4, x_6\}, \{x_3, x_7\}, \{x_8\}\}$$

(3) Classifying the attribute set U based on dual indicators yields the following conclusions.

$$\begin{aligned} U / ind(C - \{a\}) = U / \{b, c\} &= \{\{x_1, x_2, x_5\}, \{x_3\}, \{x_4, x_6\}, \{x_7\}, \{x_8\}\} \\ &\neq U / ind(C) \end{aligned}$$

$$\begin{aligned} U / ind(C - \{b\}) = U / \{a, c\} &= \{\{x_1, x_5\}, \{x_2\}, \{x_3\}, \{x_4, x_6\}, \{x_7\}, \{x_8\}\} \\ &= U / ind(C) \end{aligned}$$

$$\begin{aligned} U / ind(C - \{c\}) = U / \{a, b\} &= \{\{x_1, x_5\}, \{x_2\}, \{x_3\}, \{x_4, x_6\}, \{x_7\}, \{x_8\}\} \\ &= U / ind(C) \end{aligned}$$

Based on the results of single attributes in (1), it can be concluded that single attributes a are single attributes in the attribute set C, and they are indispensable. Attributes b and c in the attribute set can be omitted.

4) Indicator Weighting

The importance (weight) of the impact of removing a certain subset of attributes C' from the attribute set C on the decision attribute D is termed as the importance (weight), i.e., $\sigma_{CD}(C') = r_C(D) - r_{C-C'}(D)$ In calculating the brand power of new energy vehicles, the system is a non-decision system. Therefore, the importance of attributes can be represented using the following formula, as shown in Formula (8).

$$\sigma_C(C') = r_C(C) - r_{C-C'}(C) = 1 - R_{C-C'}(C) \tag{8}$$

The weight of each indicator, determined by the importance of the indicator, is normalized. The weight of the i-th indicator after normalization is given by Formula (9).

$$w_i = \frac{\sigma_C(C_i^{'})}{\sum_{i=1}^{m}\sigma_C(C_i^{'})}, i = 1, 2, \cdots, n \tag{9}$$

C. Initialization of Cellular Automata

1) Cellular Automata Features

Cellular Automata (CA) is an emerging branch of artificial intelligence and artificial life, where information processing occurs synchronously. CA is a dynamic system model in which time, space, and states are all discrete, and global changes are caused by the interaction of local cells [3].

It consists of cells, cellular space, neighbors, cell evolution rules, and cell states. CA is an information processing system composed of a large number of simple elements, simple connections, simple rules, finite states, and local interactions. It utilizes the principles and ideas of computers for system simulation and developmental prediction [4].

2) Initialization of Cellular Automata

The initialization of cellular properties in this paper is defined as follows [3-4]:

(1) Cells are defined as individual users' scores for new energy vehicle products, calculated based on Formula (9) mentioned above.

(2) Cellular space is defined as consisting of 10,000 sub-cells (100*100 in size).

(3) Cellular neighbors are defined as the four neighbors (up, down, left, right) of a cell.

(4) Cellular evolution rules are defined as passing parameters to the surrounding four neighbors based on the cell itself, with a transmission rate of 0.8. Refer to Figure 4 for the cellular evolution rules.

(5) Definition of Cellular States: Cellular states are divided into initial states and process states. The initial state is set using random numbers, while the process state is determined jointly by the initial state and the evolution rules. Assuming the first neighbor and the second neighbor are initialized with a score of 60 for the new energy product, and the parameter transmission from the first neighbor to the second neighbor is calculated at 0.8, then the second neighbor's score for the new energy product is calculated as ((60 + 60 * 0.8) / 2 = 54).

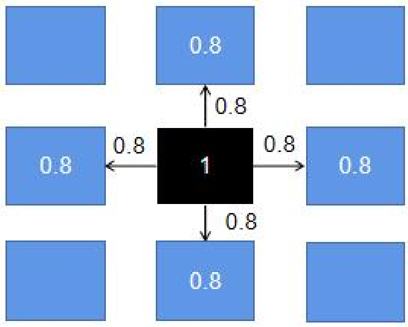

Figure 4. Illustration of Cellular Evolution Rules

3) Cellular Automaton Simulation Calculation

Based on the initialization parameters defined in section 2.2.2, this section defines the computational rules for the cellular automaton as follows:

(1) After obtaining the reduced attributes through rough set theory, initialize the scores of each indicator. Then, calculate the score of each cell (the score of each user using new energy vehicle products) by weighted sum.

(2) Simulate the scores of all users in a region for new energy vehicle products at different times within a 100*100-sized cellular space.

(3) Assume that the status (score) of all cells is computed every 1 minute. Determine the product power score of new energy vehicle products in the region based on the fitting function.

(4) Draw conclusions based on the product power scores.

III. CASE STUDY

A. Attribute Reduction

Based on the principles outlined in Section 2.2, this paper collected 10,000 characteristic data of users using the new energy product in a certain region. By discretizing continuous data, we calculated the dispensable indicators. According to the formula representing the classification of attribute sets based on the values of attributes, belonging to the set of indicators in Table 1, we classified the attribute set. After calculation, it was found that:

$$U\ /\ ind(C-\{c_i\}) = \begin{cases} \neq U\ /\ ind(C), i = 1,2,5,6,7,8 \\ = U\ /\ ind(C), i = 3,4 \end{cases} \tag{10}$$

Therefore, from equation (10), it is evident that except for the policy and subsidy factors, which can be considered as dispensable attributes, the other attributes cannot be ignored. The reduced indicator factors are presented in Table 3 below.

Table 3. Reduced Indicator Factors

Index	Indicator Factor Name
1	price
2	Driving Range
3	Charging Convenience
4	Level of Intelligence
5	Technological Innovation Capability
6	Safety Performance

Through further analysis, it is evident that the policies and subsidies related to the new energy vehicle industry in the same region are consistent. Therefore, the policy and subsidy factor indicators can be removed.

B. Initialization of Cell Scores

The score calculation formula for each cell is as follows, according to Equation (11):

$$s\_cell = \sum_{i=1}^{n} (w_i * s_i), \quad n = 1, \cdots, 6 \tag{11}$$

Where Si represents the initialized score for each cell, and wi represents the weight of each indicator for each cell (obtainable from Equation (9)).

(1) Initialization of Price Scores.

According to the maximum and minimum values, the column indicators are standardized to a range of 0-1 (using Equation (2) or Equation (3)). The standardized data are then mapped according to the mapping relationship of a maximum of 80 points and a minimum of 20 points, as shown in Equation (12).

$$y_i = 60x_i + 20 \tag{12}$$

Where xi represents the initialized data for each cell after standardization, and wi mapped represents the mapped score.

(2) Initialization of Driving Range Score.

The handling method is the same as the price initialization score.

(3) Initialization of Charging Convenience Score.

Since this data type is discrete, with only "Yes" or "No" as attribute values, it is set to 80 points for "Yes" and 20 points for "No".

(4) Initialization of Intelligence Level Score.

The intelligence level is categorized into L2, L3, and L4 levels. Therefore, this paper specifies L2=30 points, L3=50 points, and L4=70 points.

(5) Initialization of Technological Innovation Capability Score.

The technological innovation capability is categorized into low, medium, and high levels. Therefore, this paper specifies low=30 points, medium=50 points, and high=70 points.

(6) Initialization of Safety Performance Score.

The handling method is the same as the price initialization score.

C. The results of weight calculation

The weights of the simplified indicator factors obtained from the simplified attribute set are shown in Table 4 below.

Table 4. Weight of Simplified Indicator Factors

Index	Indicator Factor Name	Weight
1	Price	0.2
2	Driving Range	0.25
3	Charging Convenience	0.14
4	Intelligence Level	0.12
5	Technological Innovation	0.15
6	Safety Performance	0.14
7	Total	1

D. Dynamic Simulation of Cellular Automaton

Based on a cellular space of 10,000 sub-cells and initialized parameters, system simulation was conducted. The top 10 simulation results are shown in Table 5.

Table 5. Top 10 Scores of Simulation Results

Index	Score
1	80
2	79
3	79
4	77
5	77
6	76
7	75
8	75
9	75
10	75

On the first day, the cellular system's cell states are depicted in Figure 5. In this figure, red cells indicate that the score of the new energy vehicle products in these cells falls within the range of [75, 80]; blue cells represent a score range of [70, 75]; green cells represent a score range of [65, 70], while cells with scores outside these ranges are not displayed.

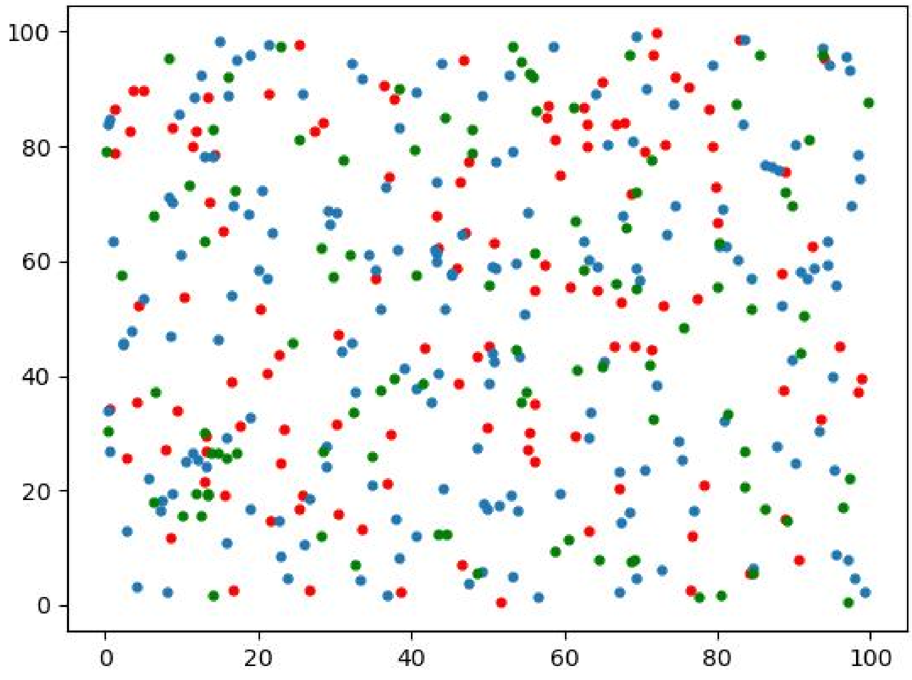

Figure 5. The cell state results of the cellular system at T=1.

On the 15th day, the cell state results of the cellular system are shown in Figure 6. The color ranges remain consistent with the previous description: red -> [75,80], blue -> [70,75], green -> [65,70]. It can be observed that after 15 days of stacking time, the state of each cell is updated, and the product strength of new energy vehicles in the region is also updated, providing insights into the product strength of new energy vehicles.

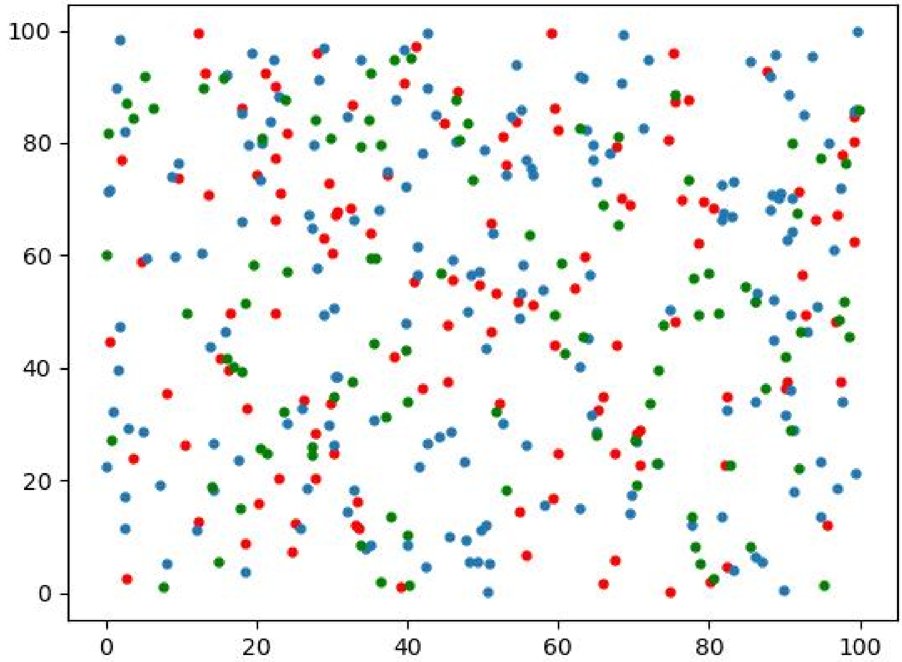

Figure 6. The cell state results of the cellular system at T=15.

E. Overall Score

Through the calculations of 10,000 sub-cells in Section 3.4, we can obtain the evaluation of the vehicle's product strength by different users of new energy vehicles in a specific region. By integrating the calculation results of all cells in this region, we can use the method of "removing the maximum and minimum values and taking the average" to calculate the overall product strength score of the brand's vehicle in this region. The calculation formula is shown in Equation (13).

$$S = \frac{\sum_{i=1}^{k} y_i}{k}, \quad k = 1, \cdots, 9998 \tag{13}$$

After removing the maximum score of 80 points and the minimum score of 20 points, according to Equation (13), we obtain S=72. This indicates that the level of acceptance of this brand in the region is relatively high.

IV. Results and Analysis

In this study, we selected data from 10,000 users of new energy vehicles in the same region. Through the proposed methodology, we can simulate and calculate the product competitiveness of new energy vehicles in real-time. While this approach can to some extent meet the needs of car companies and relevant departments in monitoring the performance of a brand in the market, there are limitations. The selection of a single region may introduce biases such as "group conformity" and "community data" effects, leading to a skewed distribution of data. In the future, the study will expand to include multiple regions to calculate the product competitiveness scores of a particular brand of new energy vehicles, thus avoiding the "community effect" and ensuring that the computed results are more aligned with the actual situation. This will contribute to the healthy and sustainable development of the automotive engineering industry.

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