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Optimizing New Energy Vehicle Supply Chain Pricing and After-sales Service Processes through Intelligent Algorithms under Different Sales Modes

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Abstract New energy vehicle industry is developing rapidly, and supply chain pricing strategy and after-sales service quality become the core competitiveness of enterprises. This paper constructs a new energy vehicle supply chain pricing and after-sales service model, and explores the supply chain pricing and profit distribution problems under different sales modes through multi-objective chaotic optimization algorithm. The study takes the manufacturer-led "1:n" type new energy vehicle supply chain as the object, analyzes the impact of three packages after-sales service on pricing and profit, and compares the effects of centralized decision-making and decentralized decision-making modes. The results show that the pricing range of the models in the centralized decision-making mode is 229,500-250,000 yuan, which is significantly lower than that of 254,600-280,000 yuan in the decentralized decision-making mode; the multi-objective chaotic optimization algorithm makes the total profit of the new energy vehicles reach 6,952,950,000 yuan, which is 432,820,000 yuan higher than that of the traditional chaotic optimization algorithm; and under the stable state of the market, the profit of the most profitable models stays stable at around 41,000,000 yuan. The study concludes that the profit distribution mechanism based on Shapley's value method can achieve a multi-win situation in the supply chain; the intelligent algorithm optimization can effectively coordinate the relationship between manufacturers and dealers and improve the overall efficiency of the supply chain; new energy vehicle enterprises should implement the optimization of the supply chain decision-making from the three aspects of the upstream product technology, the middle reaches of the production and logistics, and the downstream marketing and branding.

Index Terms new energy vehicles, supply chain pricing, after-sales service, multi-objective chaotic optimization, Shapley value, intelligent algorithm

I. Introduction

Recently, the global automotive industry has been renewed, and countries around the world have successively increased policy support and continuously improved strategic planning. Automobile enterprises increase R&D investment, optimize industrial layout, and realize transnational development. New energy has become a clear direction for the transformation of the automotive industry, as well as a major driving force for global economic growth [1]-[3]. 2020 new energy vehicle sales reached 3.1 million units, an increase of about 41% year-on-year, and the emergence of new energy vehicles has made Europe the world's first largest automotive market [4]. In the same year, China's new energy automobile industry's total import and export foreign trade also rose about 270% year-on-year [5]. China's new energy automobile market in the "policy + market" drive dual-carbon goals, showing a dominant trend from the policy to the market change, the international new energy market shows the demand for the market continues to expand the growth trend [6]-[8]. Therefore, China's automobile enterprises can not only stay in the mainland self-production and self-sale of the inner volume, the future should go out of the country and step into the international market. At the same time, enterprise channel decisions and pricing decisions in the automotive supply chain determine the market dynamics, and the impact of different sales channels on the development of automotive supply chain is becoming more and more prominent [9], [10].

The automotive supply chain channel is the lifeblood of the automotive market, and at present, China's automotive industry is mainly dominated by 4S outlets as the sales model [11]. However, driven by Internet technology, the supply chain sales model is becoming more and more diversified [12]. Nowadays, Volvo and other automobile manufacturers have adopted the dual-channel sales model of "online direct sales + offline experience" to build a network channel that is different from the traditional retail channel, which realizes more diversified services for consumers and a supply chain layout that conforms to the development of the times [13]-[15]. Upstream enterprises have made every effort to develop clean energy and green power to realize the industrial docking of energy and transportation. Downstream enterprises use market regulation, policy propaganda and other means to create online channels to reduce sales costs and increase channel diversification, which helps to promote the popularization of new energy vehicles [16]-[18]. However, the diversified sales model has also exacerbated the problem of enterprise decision-making, and channel decision-making in different business scenarios is the key to maximize the interests of enterprises and maximize consumer satisfaction [19]-[21]. Therefore, there is an urgent need for member companies of the automotive supply chain to develop reasonable pricing strategies to adapt to the complex demand market [22].

Accompanied by the rising popularity of new energy vehicles, after-sales service demand also presents different characteristics from traditional fuel vehicles. The after-sales service system of traditional fuel vehicles has formed a set of mature service model and supply chain system after a long period of development [23], [24]. However, this system is not fully applicable to new energy vehicles because there are essential differences in technology, maintenance and service needs between the two [25]. Customers' expectations of after-sales service are also increasing, especially in the field of new energy vehicles. Therefore, in the rapid development of the new energy vehicle industry, after-sales service has become one of the key elements of brand competitiveness [26].

In recent years, the global energy shortage and environmental problems have become increasingly severe, and new energy vehicles, as a substitute for traditional fuel vehicles, have gradually become an important direction for the development of the automobile industry. Governments have introduced policies to support the development of the new energy vehicle industry, and the market scale has been expanding and the competition has become increasingly fierce. In this context, new energy vehicle enterprises are facing the challenges of how to improve product competitiveness, optimize supply chain management and enhance service quality. Supply chain management, as the core link of enterprise operation, its efficiency and quality directly affect the profitability and market performance of enterprises. Especially in the emerging industry of new energy vehicles, supply chain management faces more uncertainties due to the diverse technology routes and complex industrial chain. The supply chain pricing strategy and after-sales service process are the key factors affecting consumers' purchasing decision and brand loyalty, which have an important impact on the long-term development of the enterprise.

The supply chain of new energy vehicles usually consists of manufacturers, dealers and consumers, and the decision-making behaviors and strategy choices of each party constitute a complex gaming system. In the decentralized decision-making mode, manufacturers and dealers pursue profit maximization individually, which often leads to inefficiency of the supply chain as a whole; while in the centralized decision-making mode, the coordination of all parties' behaviors can realize the improvement of the overall efficiency of the supply chain. However, how to design a reasonable pricing strategy and benefit distribution mechanism so that all parties voluntarily participate in the coordination mechanism has become the focus of attention of academia and industry. In addition, the implementation of “three packs” after-sales service, as a mandatory requirement in the automobile industry, is directly related to the protection of consumers' rights and interests and the reputation of enterprises, but it also increases the operating costs of enterprises. Therefore, how to formulate the optimal pricing strategy to balance the interests of all parties under different after-sales service modes is an issue worthy of in-depth discussion.

Traditional research mainly focuses on the pricing strategy under a single decision-making mode, and there are fewer studies that comparatively analyze the pricing problems under different decision-making modes and after-sales service modes. Meanwhile, the development of artificial intelligence and big data technology makes the application of intelligent optimization algorithms in supply chain management promising, but the research on the practical application in supply chain optimization of new energy vehicles is still insufficient. Therefore, this study will explore the methods and effects of optimizing the pricing and after-sales service processes of new energy vehicle supply chain through intelligent algorithms under different sales models. This paper takes the manufacturer-led “1:n” new energy vehicle supply chain as the research object, constructs a supply chain pricing model considering after-sales service factors, and solves the problem by using the multi-objective chaotic optimization algorithm. Firstly, the decentralized decision-making model under four different after-sales service modes is analyzed to compare the impacts of different after-sales service strategies chosen by the manufacturer and distributor on pricing and profit; secondly, the centralized decision-making model is established to explore the role of coordination mechanism in improving the overall efficiency of the supply chain; finally, the benefit distribution mechanism is designed based on the Shapley's value method to ensure that all parties receive fair and reasonable profit distribution. The effectiveness of the model is verified through actual case data simulation, and targeted supply chain decision-making suggestions are put forward to provide theoretical guidance and practical reference for new energy automobile enterprises.

II. New Energy Vehicle Supply Chain Pricing and After-sales Service Modeling

The after-sales service process of new energy vehicles mainly includes the repair, replacement and return of automobile products (hereinafter referred to as “three packages”), this paper considers the three packages of new energy vehicles, constructs the pricing and after-sales service model of new energy vehicle supply chain, and adopts the chaotic optimization algorithm to optimize the solution.

II. A. Problem description and notation

II. A. 1) Description of the problem

Taking the “1:n” type new energy vehicle supply chain, in which the manufacturer dominates the production of a single product, as the research object, decentralized decision-making is used to study the impact of three packages of after-sales service on the pricing and profit of the supply chain of new energy vehicles, and then centralized decision-making is used to improve the Pareto of the supply chain, and finally, the profit of the supply chain under the centralized decision-making is rationally distributed. Then the supply chain Pareto is improved through centralized decision-making, and finally the supply chain profit is rationally distributed under centralized decision-making.

II. A. 2) Notation and description of constraints

(1) Explanation of symbols

c_0 - Manufacturing cost.

c_i -Distribution cost of distributor i.

c_w -Unit product three packages after-sale cost.

C_w -Unit product three packages after-sale cost (including penalty).

a - Three-package after-sales service penalty factor.

μ -value amplification factor.

D_i -Demand of dealer i.

Q -Maximum manufacturer's output.

w_i -wholesale price of distributor i.

p_i -Distributor i selling price.

π_m - Manufacturer's profit.

π_n -Dealer i profit.

π_i - Manufacturer's profit with distributor i.

π - Supply chain profit.

(2) Statement of basic constraints

a) The manufacturer's maximum output is Q, i.e., $\sum_{i=1}^{n} D_i \le Q$.

b) The manufacturer's wholesale price is limited to $w_i \le w_i \le \overline{w_i}$.

c) To have their own profit, dealers should fulfill the restriction of $p_i > w_i$.

d) With the continuous promotion of after-sales service, the whole new energy vehicle market becomes more standardized, the reputation of manufacturers and dealers improves, and customer loyalty increases. The amplification coefficient of three-package after-sales service on the tangible value chain is μ, which satisfies $\mu > 1$.

e) The “three packages after-sales service” is a mandatory requirement, and operators will be fined with a penalty coefficient of a if they fail to fulfill the requirement, satisfying $a > 1$.

f) After-sales costs are shared between the manufacturer and the distributor according to the proportion of responsibility, the manufacturer's share is k, then the distributor's share is $1-k$, satisfying $0 \le k \le 1$.

g) In the overall profit sharing of supply chain cooperation, using the Shapley value method, it satisfies $V(\varnothing) = 0, V(S_1 \cup S_2) \ge V(S_1) + V(S_2), S_1 \cap S_2 = varnothing$.

II. B. Supply Chain Demand Functions

Define the demand function of dealer i in the automotive supply chain as:

$$\begin{aligned} D_i(p_i, p_{-i}) = D_0(i) - \alpha_i p_i + \beta_{1i}(p_1 - p_i) + \beta_{2i}(p_2 - p_i) \\ + \beta_{3i}(p_3 - p_i) + \cdots + \beta_{ni}(p_n - p_i) \end{aligned} \tag{1}$$

Eq. (1) can be simplified as:

$$D_i(p_i, p_{-i}) = D_0(i) - \alpha_i p_i + \sum^{n} \beta_{ii}(p_l - p_i) \tag{2}$$

where: $-i$ denotes distributors other than distributor i, $D_0(i)$ refers to the market capacity of the region where distributor i is located, α_i is the consumer's sensitivity to the price of distributor i, and β_{ij} denotes the price of distributor i of the distributor coefficient of demand impact on distributor j and satisfies: $\alpha_i > 0, \beta_{ij} \geq 0, \beta_{ji} \geq 0$.

II. C.Integrated value model for supply chain members

The integrated value model of the supply chain under the construction of after-sales service is constructed as follows:

Manufacturer profit:

$$\pi_m(w_i) = \mu \sum_{i=1}^{n} (w_i - c_0 - c_i - kc_w) D_i \tag{3}$$

Dealer i profit:

$$\pi_n(p_i) = \mu[p_i - w_i - (1-k)c_w] D_i \tag{4}$$

where $\pi_m(w_i), \pi_n(p_i)$ are the profits of the manufacturer and the distributor i respectively, i.e., the combined value of the manufacturer and the distributor i. μ is the amplification factor of the intangible value created by after-sales service to the tangible value chain.

$\sum_{i=1}^{n}(w_i - c_0 - c_i - kc_w)D_i, [p_i - w_i - (1-k)c_w]p_i$ for manufacturer respectively and distributor i's production function of the tangible value chain, i.e., it is the production function when no after-sales service is provided.

II. D.Supply Chain Pricing and Benefit Alignment Models

II. D. 1) Decentralized decision-making models

According to whether manufacturers and distributors in the supply chain choose to comply with the “three packs” after-sales service, there are four types of sales models: manufacturers and distributors comply, manufacturers and distributors do not comply, manufacturers do not comply, distributors comply, and manufacturers comply, distributors do not comply.

(1) Manufacturers and dealers comply with after-sales service at the same time

Manufacturers and distributors according to the three packages of after-sales service responsibility ratio share after-sales service costs, and will not be subject to the relevant penalties, exempt from the relevant government departments fines, that is, the manufacturer of the unit product to bear the cost of after-sales service for kc_w, the distributor of the unit product to bear the cost of after-sales service for $(1-k)c_w$.

When both the manufacturer and the dealer comply with the after-sales service regulations, the new energy vehicle supply chain model takes into account the new cost and intangible value created by the after-sales service to the operator to construct the pricing model:

$$\max \pi_m^{\ 1}(w_i) = \mu \sum_{i=1}^{n} (w_i - c_0 - c_i - kc_w) D_i \tag{5}$$

$$\begin{gathered} \max \pi_{ri}^{\ 1}(p_i) = \mu[p_i - w_i - (1-k)c_w] D_i \\ S.t\ w_i \leq w_i \leq \overline{w_i} \\ p_i > w_i \\ \sum_{i=1}^{m} D_i \leq Q \end{gathered} \tag{6}$$

where $\mu > 1$.

Assuming that the function $\pi_n^1(p_i)$ is everywhere minimizable, by first-order partiality conditions $\frac{\partial \pi_{ii}^1(p_i)}{\partial p_i}=0$ for p_i, we have $p_i=\frac{1}{2}\left[\frac{D_0(i)+\sum_{l=1 \text{ and } l\neq i}^{n}\beta_{li}p_l}{\alpha_i+\sum_{l=1 \text{ and } l\neq i}^{n}\beta_{li}}+w_i+(1-k)c_w\right]$, and the association $p_1,p_2,\cdots,p_n$ solves $p_i^*(w_1,w_2,\cdots,w_n)$, which carries p_i^* into the upper planning objective function:

$$\begin{aligned}\max \pi_m^1(w_i)&=\mu\sum_{i=1}^{n}(w_i-c_0-c_i-kc_w)D_i\\&=\mu\sum_{i=1}^{n}(w_i-c_0-c_i-kc_w)\left[D_0(i)-\alpha_i p_i+\sum_{l=1 \text{ and } l\neq i}^{n}\beta_{li}(p_i-p_i)\right]\\&=\mu\sum_{i=1}^{n}(w_i-c_0-c_i-kc_w)\left[D_0(i)-\alpha_i p_i^*+\sum_{l=1 \text{ and } l\neq i}^{n}\beta_{li}(p_i^*-p_i^*)\right]\end{aligned} \tag{7}$$

(2) Manufacturers and distributors do not comply with after-sales service

Manufacturers and dealers do not need to bear the after-sales service cost, but must be penalized by a fine with a penalty coefficient of $a(a>1)$ on top of the after-sales service cost as stipulated by the relevant government departments, i.e., the after-sales service fine per unit of the manufacturer's product is akc_w, and that per unit of the dealer's product is $a(1-k)c_w$.

The new energy vehicle supply chain model takes into account the after-sales service penalty to construct the pricing model when both the manufacturer and the dealer do not comply with the after-sales service regulations:

$$\max \pi_m{}^2(w_i)=\sum_{i=1}^{n}(w_i-c_0-c_i-akc_w)D_i \tag{8}$$

$$\begin{gathered}\max \pi_{ri}{}^2(p_i)=[p_i-w_i-a(1-k)c_w]D_i\\ S.t\ w_i\le w_i\le \overline{w_i}\\ p_i>w_i\\ \sum_{i=1}^{m}D_i\le Q\end{gathered} \tag{9}$$

where $a>1$.

Assuming that the function $\pi_{ri}^2(p_i)$ is everywhere minimizable, by a first-order partiality condition $\frac{\partial \pi_{ri}^2(p_i)}{\partial p_i}=0$ for p_i, there is $p_i=\frac{1}{2}\left[\frac{D_0(i)+\sum_{l=1 \text{ and } l\neq i}^{n}\beta_{li}p_l}{\alpha_i+\sum_{l=1 \text{ and } l\neq i}^{n}\beta_{li}}+w_i+a(1-k)c_w\right]$, and associating $p_1,p_2,\cdots,p_n$ solves $p_i^*(w_1,w_2,\cdots,w_n)$, which carries p_i^* into the upper planning objective function:

$$\begin{aligned}\max \pi_m^2(w_i) &= \mu\sum_{i=1}^{n}(w_i - c_0 - c_i - akc_w)D_i n \\ &= \mu\sum_{i=1}^{n}(w_i - c_0 - c_i - akc_w)\left[D_0(i) - \alpha_i p_i + \sum_{l=1 \text{ and } l\neq i}^{n} \beta_{li}(p_l - p_i)\right] \\ &= \mu\sum_{i=1}^{n}(w_i - c_0 - c_i - akc_w)\left[D_0(i) - \alpha_i p_i^* + \sum_{l=1 \text{ and } l\neq i}^{n} \beta_{li}(p_l^* - p_i^*)\right]\end{aligned} \tag{10}$$

(3) Manufacturer's non-compliance and distributor's compliance with after-sales service

The distributor shares all the after-sales service costs while the manufacturer does not bear the after-sales service costs. Under the hypothetical after-sales service penalty reward and punishment mechanism, the manufacturer will be penalized by a fine with a penalty coefficient of $a(a>1)$ for non-compliance with the after-sales service regulations akc_w, and the distributor, although he shares all the after-sales service costs of a unit of the product c_w, he will be rewarded with the full amount of after-sales service penalty akc_w that the government collects from the manufacturer. Pricing modeling:

$$\max \pi_m{}^3(w_i) = \mu\left[\sum_{i=1}^{n}(w_i - c_0 - c_i - kc_w)D_i\right] + (1-a)kc_w\sum_{i=1}^{n} D_i \tag{11}$$

$$\begin{gathered}\max \pi_{ri}{}^3(p_i) = \mu[p_i - w_i - (1-k)c_w]D_i + (a-1)kc_w D_i \\ S.t\ w_i \le w_i \le \overline{w_i} \\ p_i > w_i \\ \sum_{i=1}^{m} D_i \le Q\end{gathered} \tag{12}$$

where $\mu > 1$.

Assuming that the function $\pi_n^3(p_i)$ is everywhere minimizable, by the first-order partiality condition $\frac{\partial \pi_{ri}^3(p_i)}{\partial p_i} = 0$ for p_i, there is a $p_i = \frac{1}{2}\left[\frac{D_0(i) + \sum_{l=1 \text{ and } l\neq i}^{n} \beta_{li} p_i}{\alpha_i + \sum_{l=1 \text{ and } l\neq i}^{n} \beta_{li}} + w_i + (1-k)c_w + \frac{(1-a)kc_w}{\mu}\right]$, associating $p_1, p_2, \cdots, p_n$ solves for $p_i^*(w_1, w_2, \cdots, w_n)$, which carries p_i^* into the upper level planning objective function:

$$\begin{aligned}\max \pi_m^3(w_i) &= \mu[\sum_{i=1}^{n}(w_i - c_0 - c_i - kc_w)D_i] + (1-a)kc_w\sum_{i=1}^{n} D_i \\ &= \left[\mu\sum_{i=1}^{n}(w_i - c_0 - c_i - kc_w) + (1-a)kc_w\right]\left[D_0(i) - \alpha_i p_i + \sum_{l=1\ and\ l\neq i}^{n} \beta_{li}(p_l - p_i)\right] \\ &= \left[\mu\sum_{i=1}^{n}(w_i - c_0 - c_i - kc_w) + (1-a)kc_w\right]\left[D_0(i) - \alpha_i p_i^* + \sum_{l=1\ and\ l\neq i}^{n} \beta_{li}(p_l^* - p_i^*)\right]\end{aligned} \tag{13}$$

(4) Manufacturer's compliance and dealer's non-compliance with after-sales service

Construct a pricing model when the manufacturer complies and the distributor does not comply with after-sales service regulations:

$$\max \pi_m^4(w_i) = \sum_{i=1}^{n}(w_i - c_0 - c_i)D_i \tag{14}$$

$$\begin{gathered}\max \pi_{ri}{}^{4}(p_i) = (p_i - w_i - ac_w)D_i \\ S.t\ w_i \le w_i \le \overline{w_i} \\ p_i > w_i \\ \sum_{i=1}^{m} D_i \le Q\end{gathered} \tag{15}$$

where $a > 1$.

Assuming that the function $\pi_{ri}^{4}(p_i)$ is everywhere minimizable, by first-order partiality conditions $\frac{\partial \pi_{ri}^{4}(p_i)}{\partial p_i} = 0$ for p_i, we have $p_i = \frac{1}{2}\left[\frac{D_0(i) + \sum_{l=1\ and\ l \ne i}^{n} \beta_l p_l}{\alpha_i + \sum_{l=1\ and\ l \ne i}^{n} \beta_{li}} + w_i + ac_v\right]$, and associating $p_1, p_2, \cdots, p_n$ solves $p_i^{*}(w_1, w_2, \cdots, w_n)$, and carry p_i^{*} to the upper planning objective function:

$$\begin{aligned}\max \pi_{m}^{4}(w_i) &= \sum_{i=1}^{n}(w_i - c_0 - c_i)D_i \\ &= \sum_{i=1}^{n}(w_i - c_0 - c_i)\left[D_0(i) - \alpha_i p_i + \sum_{l=1\ and\ l \ne i}^{n} \beta_h (p_l - p_i)\right] \\ &= \sum_{i=1}^{n}(w_i - c_0 - c_i)\left[D_0(i) - \alpha_i p_i^{*} + \sum_{l=1\ and\ l \ne i}^{n} \beta_h (p_l^{*} - p_i^{*})\right]\end{aligned} \tag{16}$$

II. D. 2) Centralized decision-making models

Take the new energy vehicle supply chain members all comply with the after-sales service situation as an example, establish the new energy vehicle supply chain cooperation game model, and there exist w_i and p_i so that the following model has an optimal solution:

$$\max \pi(w_i, p_i) = \mu \sum_{i=1}^{n}\{(w_i - c_0 - c_i - kc_w)D_i + [p_i - w_i - (1-k)c_w]D_i\} \tag{17}$$

Eq. (17) can be simplified as:

$$\begin{gathered}\max \pi(w_i, p_i) = \mu \sum_{i=1}^{n}(p_i - c_0 - c_i - c_w)D_i \\ S.t.\ \underline{w_i} \le w_i \le \overline{w_i} \\ p_i > w_i \\ \sum_{i=1}^{n} q_i \le Q\end{gathered} \tag{18}$$

Of these, $\mu > 1$.

II. D. 3) Modeling the distribution of benefits from cooperative games

Combined with the Shapley value profit sharing mechanism, the new energy vehicle supply chain manufacturer and n dealers constitute the supply chain member set I, with 0 representing the manufacturer and $1, 2, \cdots, i, \cdots, n$ representing the dealers, i.e. $I = \{0, 1, 2, \cdots, n\}$.

In the first step, determine the possible cooperation scale, cooperation scheme and corresponding cooperation profit of all members in the supply chain.

The second step is to determine the various possibilities and corresponding probabilities of all dealers in the supply chain cooperation, their contribution and value in the cooperation. The formula for calculating the probability of cooperation form is as follows:

$$W(|S|)=\frac{1}{(n+1)C_n^k} \tag{19}$$

When calculating the probability of a dealer's cooperation pattern, k indicates the number of dealers that work with the manufacturer along with dealer i. When calculating the probability of the manufacturer's cooperation mode, k indicates the number of dealers that cooperate with the manufacturer.

In the third step, various possibilities and corresponding probabilities of the manufacturer's contribution and value in the supply chain cooperation are determined. Based on the unique indicator vector of the value of each game party $(\varphi_1,\varphi_2,\cdots,\varphi_n)$, where $\varphi_i(V)=\sum W(|s|)[V(s)-V(s\setminus\{i\})]$, $W(|s|)$ is equation (19), which gives the profit of the manufacturer and all distributors:

$$\begin{aligned}\pi_m^{'}=&\frac{1}{n+1}\pi_m+\frac{1}{(n+1)c_n^1}(\pi_1+\sum_{r=2}^{n}\pi_{ml}-\pi_{r1})\\&+\cdots+\frac{1}{(n+1)c_n^1}(\pi_n+\sum_{l=1}^{n}\pi_{ml}-\pi_m)+\frac{1}{(n+1)c_n^2}(\pi_1+\pi_2+\sum_{l=3}^{n}\pi_{ml}-\pi_{r1}-\pi_{r2})\\&+\cdots+\frac{1}{(n+1)c_n^2}(\pi_{n-1}+\pi_n+\sum_{l=1}^{n}\pi_{ml}-\pi_{m-1}-\pi_m)\\&+\cdots+\frac{1}{n+1}\sum_{i=1}^{n}(\pi_i-\pi_{rn})\end{aligned} \tag{20}$$

$$\pi_{ri}^{'}=\frac{1}{1+n}\pi_{ri}+\frac{n}{1+n}(\pi_i-\pi_{mi}) \tag{21}$$

II. E. Multi-objective chaotic optimization algorithm

Multi-objective chaotic optimization algorithm is used in this paper to solve the new energy vehicle supply chain pricing and after-sales service model. The multi-objective optimization problem requires a set of optimal solutions, and the set of optimal solutions is called the Pareto optimal solution set. For the multi-objective optimization problem, it can be described by the following mathematical model:

$$\begin{cases}min\vec{f}(\vec{x})=\{f_1(\vec{x}),f_2(\vec{x}),\ldots,f_k(\vec{x})\}^T\\ s.t.\quad \vec{x}\subset S\subset R^n\end{cases} \tag{22}$$

where $k\geq 2$, $\vec{f}(x)$ denotes a vector consisting of k objective functions that need to be optimized simultaneously, and the decision variable $\vec{x}=(x_1,x_2,\ldots x_n)^T$ with a range of variation S.

Although the chaotic optimization algorithm achieves good results when used to optimize a single objective function, it is mainly used to optimize a single-objective optimization problem with only one objective function, and is not suitable for solving a multi-objective optimization problem with a set of Pareto optimal solutions. This subsection applies chaos to multi-objective optimization problems by introducing crossover operations, merge operations, and adaptively varying noise.

II. E. 1) Cross-operation

The chaotic sequence obtained by chaotic mapping has a relatively large difference between two consecutive chaotic variables in the sequence, which makes the decision variables vary more, which on the one hand facilitates the algorithm to perform a global search and is not easy to fall into a local optimum, but on the other hand, the algorithm's ability to perform local searches is correspondingly weakened. By using the crossover operation, the optimization variables of two parallel solutions are exchanged and a new solution can be generated.

Assuming that the population size of the algorithm is p, the crossover of two parallel solutions in the population is performed to generate a new solution as follows:

$$x_{i,j}^{C} = \begin{cases} x_{mj}, m \in (1,2,...,p), if\ x_{ij}\ is\ chosen\ to\ be\ crossed \\ x_{ij}, otherwise \end{cases} \tag{23}$$

II. E. 2) Merge operations

Due to the large step size of chaotic motion, even if the chaotic optimization algorithm has searched the suboptimal solution near the global optimal solution, it still needs to iterate the search for many times to find the global optimal solution. In order to improve the development ability of the chaotic optimization algorithm, the merge operation is used to generate new solutions, i.e., the optimization variables of the parallel solutions in the population are merged with the optimization variables of the current optimal solutions in the population, and the specific operation of the merge operation to generate new solutions is shown below:

$$x_i = \gamma * x_i + (1-\gamma) * x_i^* \tag{24}$$

where x_i denotes the i th variable of the new solution, and γ is the chaotic variable, generated by the logistic mapping, as follows:

$$\gamma_{n+1} = 4\gamma_n(1-\gamma_n), \gamma_n \in (0,1) \tag{25}$$

II. E. 3) Adaptive noise

During the search process of multi-objective chaotic optimization algorithm, the search efficiency of the multi-objective chaotic optimization algorithm can be improved on one hand by adding adaptive changing noise at different stages of the search; on the other hand, the adaptivity of the multi-objective chaotic optimization algorithm is strengthened, which makes the algorithm able to optimize for different multi-objective optimization problems without adjusting the control parameters. The magnitude of the adaptive noise is shown below:

$$Noise = F_{j,t} * \sqrt{VAR_j} * (\gamma - 1) \tag{26}$$

That is, the magnitude of noise added to the j th optimization variable at the t th iteration is proportional to the variance of the j th optimization variable in the population. Where $F_{j,t}$ is the parameter that controls the size of the noise added to the j th optimization variable at the t th iteration, and the magnitude of the value of $F_{j,t}$ is related to the change in the variance of the j th optimization variable, as follows:

$$F_{j,t} = \begin{cases} U[F_{\min 1}, F_{\max 1}]; VAR_{j,t} < VAR_{j,t-1} < \cdots < VAR_{j,t-\partial} \\ U[F_{\min 2}, F_{\max 2}]; VAR_{j,t} > VAR_{j,t-1} > \cdots > VAR_{j,t-\beta} \end{cases} \tag{27}$$

II. E. 4) Renewal of populations

In each iteration, the matrix X_{new} consisting of the P newly generated parallel solutions is merged with the matrix $x_{\min}$ consisting of the P optimal solutions in the current population to form the matrix x_{merge} containing 2P feasible solutions, and then all the feasible solutions in X_{merge} are subject to a Undominated ordering. The non-dominated sorting operation is able to calculate the fitness values corresponding to all feasible solutions in the matrix, thus determining the fitness of each feasible solution in the population. Finally, all feasible solutions are sorted in order of fitness value from smallest to largest, and the better P feasible solutions from X_{merge} are selected and stored in $X_{\min}$. In order to be able to accurately select P better feasible solutions from X_{merge} to be stored in $X_{\min}$, feasible solutions with the same fitness value are processed using a truncation mechanism.

Non-dominated sorting refers to a layer-by-layer process of classifying the feasible solutions in the population and determining the fitness values of the solutions based on the classification results. The specific process is as follows: firstly, all the non-dominated solutions in the current population are classified into the first layer, i.e., all the non-dominated solutions have a fitness of 1. Subsequently, the non-dominated solutions with a fitness of 1 are eliminated, and the fitness of all the non-dominated solutions among the remaining ones is set to 2. By analogy, the fitness values of all the feasible solutions in the population are determined.

II. E. 5) Algorithm flow

When chaos is used to optimize a multi-objective optimization problem, the global search capability of the algorithm is improved by employing parallel chaotic search. The development capability of the algorithm is enhanced by introducing crossover and merge operations. In addition, by adding adaptively changing noise, the algorithm becomes more adaptive and is able to optimize for different optimization problems.

Figure 1 shows the flow of the multi-objective chaotic optimization algorithm, in which NI and N denote the number of iterations, where N is set to be 500 and N1 is set to be 375, P_{map} denotes the probability that the optimization variable is generated by chaotic isthmus, P_{cross} denotes the probability that the optimization variable is generated by the crossover operation, and P_{merge} denotes the optimization variable out the probability generated by the merge operation. Similar to the case of adaptive noise variation, the magnitude of the value of the crossover operation probability P_{cross} is related to the variation of the variance of the optimization variables in the population, as shown below:

$$P\_cross_{(j,t)} = \begin{cases} U[P\_cross_{\min 1}, P\_cross_{\max 1}]; VAR_{j,t} < VAR_{j,t-1} < \cdots < VAR_{j,t-\partial} \\ U[P\_cross_{\min 2}, P\_cross_{\max 2}]; VAR_{j,t} > VAR_{j,t-1} > \cdots > VAR_{j,t-\beta} \end{cases} \tag{28}$$

As the variance of the optimized variables in the population becomes smaller and smaller, the probability of generating optimized variables from crossover operations decreases, and the probability of generating optimized variables from chaotic mapping or merge operations increases, as shown below:

$$P_{merge} + P_{cross} = 1 \tag{29}$$

$$P_{map} + P_{cross} = 1 \tag{30}$$

Similarly, as the variance of the optimized variables in the population grows larger, the probability of generating optimized variables from the crossover operation increases, while the probability of generating new optimized variables from the chaotic mapping or merging operation decreases.

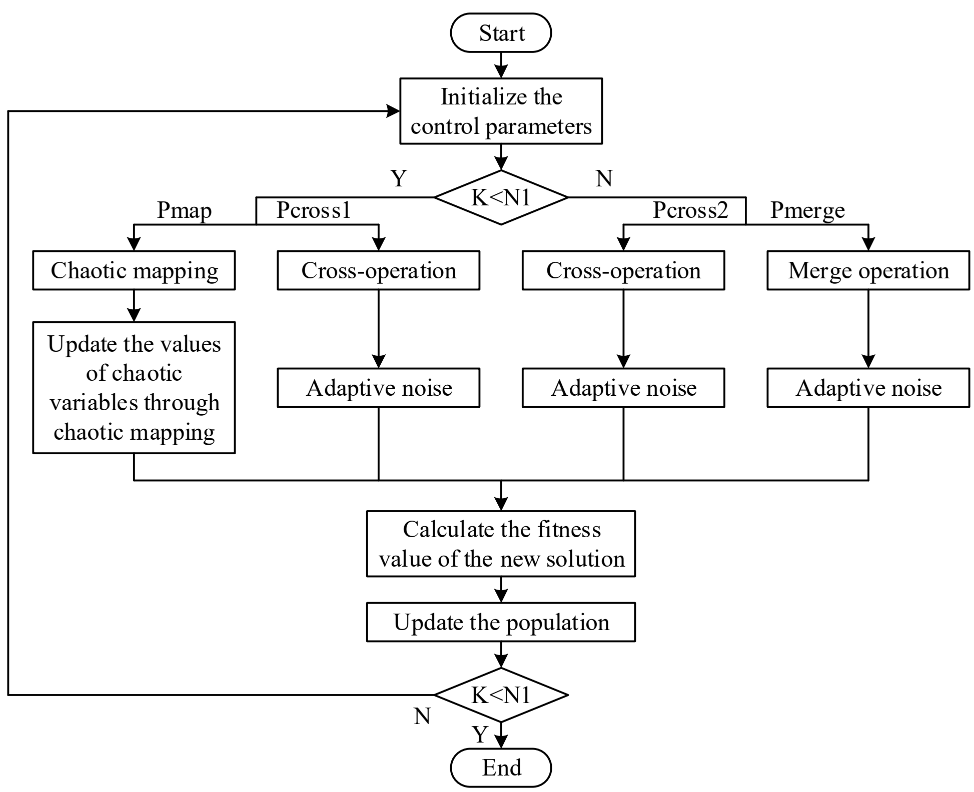

Figure 1: The process of multi-target chaotic optimization algorithm

III. Simulation model analysis

Based on the data of enterprise A, Anylogic is used as the platform to model and perform simulation analysis. A total of 145,800 consumers who have the intention to purchase a car are set up with the sales data of new energy vehicle market in 2022 as the base.

III. A. Model validation

In the simulation model, in order to verify the rationality of the new energy vehicle supply chain pricing and after-sales service model, the actual sales of each model of the enterprise are simulated and compared on the basis of 145,800 potential consumers in 2022, and the results of the comparison between the simulation sales and the actual sales are shown in Figure 2. The comparison shows that the overall trend of the simulation sales and the actual sales in 2022 is consistent, and the overall error mean value of all models is 3.39%, indicating that the simulation model of the new energy vehicle supply chain established is more stable. Therefore, the model can be used for the simulation and analysis of manufacturer learning behavior.

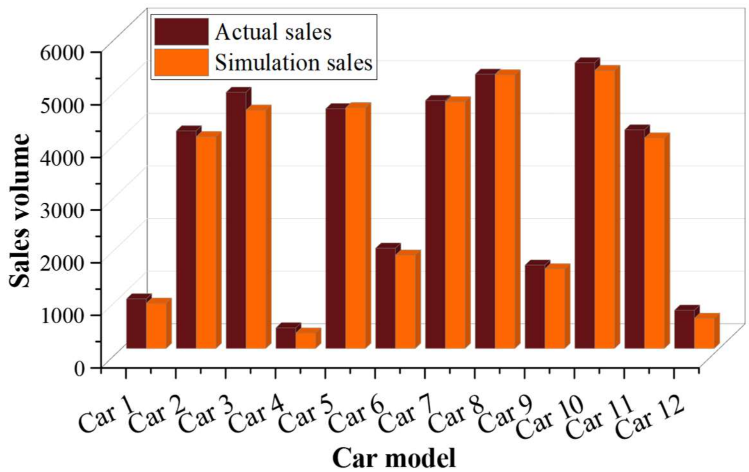

Figure 2: Comparison results of simulation sales and actual sales

III. B. Analysis of simulation results

The multi-objective chaotic optimization algorithm is used to solve the model and obtain the changes in the price and profit of each model of the new energy vehicle manufacturer. The changes in the price of each model of the manufacturer are shown in Figure 3, the changes in the price corresponding to the model with the largest profit are shown in Figure 4, and the changes in the total profit of the model with the largest profit are shown in Figure 5. After a certain period of time, the overall price of models in the middle and low price ranges increased, the price of models in the high price range increased insignificantly, and the prices of all models stabilized, with the pricing located between 250,000 and 400,000 yuan. While the price of each model stabilizes, the price corresponding to the model with the largest profit also stabilizes, making the total profit corresponding to the model with the largest profit of the manufacturer also stabilizes, and both of them eventually stabilize at around 300,000 yuan and 41 million yuan. The simulation results illustrate that the multi-objective chaotic optimization algorithm can make the new energy vehicle supply chain pricing to a stable state under the steady state of the market. The simulation results of chaotic optimization algorithm and multi-objective chaotic optimization algorithm are compared, and the data comparison of the simulation results of the two models is shown in Table 1. The total sales volume and total profit of new energy vehicles under the multi-objective chaotic optimization algorithm are improved compared with the chaotic optimization algorithm, and the total sales volume and total profit are 51,796 units and 695,295,000 yuan, respectively. The simulation of the multi-objective chaotic optimization algorithm meets the needs of differentiated development of each model, and is more suitable to be used in the adjustments of the manufacturer's pricing decision of the supply chain of new energy vehicles.

Table 1: Comparison of three model simulation results data

Model	Total sales	Gross profit/10000yuan	Average vehicle price/10000yuan
Chaos optimization algorithm	48842	652013	26.45
Multi-target chaos optimization algorithm	51796	695295	25.89

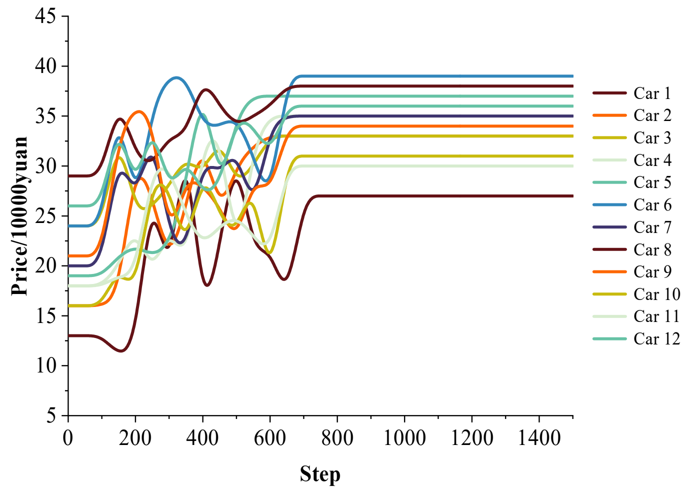

Figure 3: The price changes of the manufacturer's models

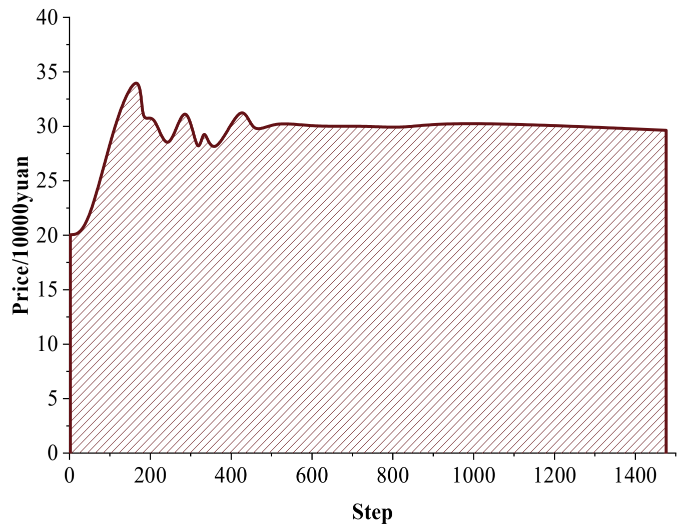

Figure 4: Price changes corresponding to the biggest profit car

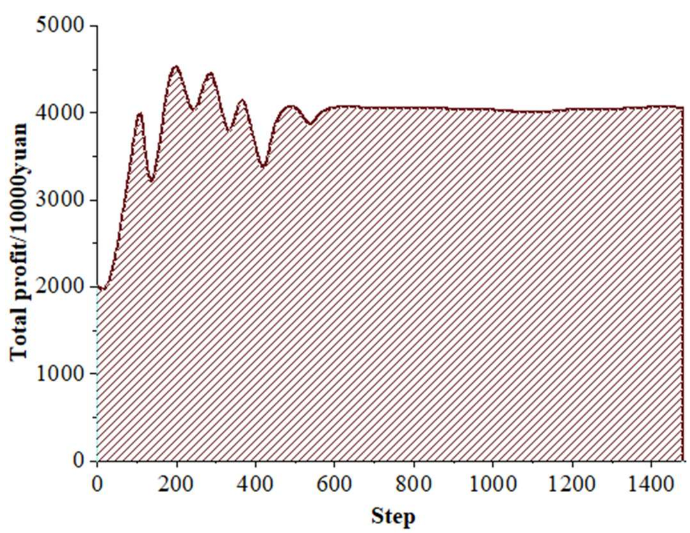

Figure 5: Total profit changes of the biggest profits car

III. C. Impact of different modes of decision-making

Analyze the change of supply chain price decision-making under centralized and decentralized decision-making respectively, and analyze theoretically that when the consumer demand increases inches, the price and revenue of the supply chain new energy vehicle products also decrease. For Company A, the correlation between price and consumer demand is drawn under this value, and the pricing of new energy vehicles under the two decision-making methods is shown in Figure 6. As can be seen from the graph, the price of new energy vehicles decreases with the increase of fee consumer demand, the price of centralized decision-making is less than the price under decentralized decision-making, and the pricing range of the two is 254,600~280,000 yuan and 229,500~250,000 yuan. Numerical simulation results prove that the centralized decision-making realizes Pareto improvement, and the supply chain profit distribution under centralized decision-making using Shapley's value method can realize a multi-win situation in the supply chain.

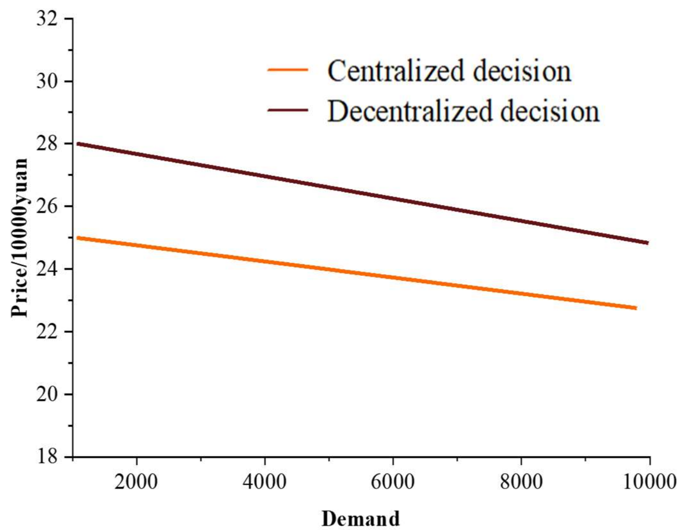

Figure 6: New energy car pricing in two ways

IV. Decision-making suggestions for new energy vehicle supply chain

IV. A. Upstream products and technologies

There are three supply chain decisions that can be made in the new energy vehicle industry in terms of product development: first, extensive market research. Consumers are able to express their needs for product functions, performance, safety, life span, appearance, etc. to manufacturers through market research, and manufacturers are also able to understand the new technologies, materials, and processes currently used in the industry by means of market research. Secondly, R&D feasibility analysis report. A comprehensive feasibility analysis report will greatly reduce the manufacturer's later production and operation costs. Third, improve product inspection standards. Manufacturers need to establish complete inspection standards and evaluation systems in the early simulation stage to meet the performance targets of new energy vehicles, so as to provide consumers with a quality product experience. Secondly, the new energy vehicle industry can realize the optimization and upgrading of supply chain decision-making in the field of technology research and development, including battery self-research and supply chain technology cooperation. Manufacturers through the strong combination of ways to promote the supply chain technology research and development, can also play an optimization of the new energy vehicle market supply chain decision-making effect.

IV. B. Midstream production and logistics

New energy vehicle enterprises should continue to explore new development paths, timely update equipment, optimize the process, to ensure that the enterprise green production targets. As today's consumers pay more and more attention to green consumption, the implementation of green production by manufacturers will, to a certain extent, increase the social value of their products, on the one hand, promote the growth of market sales, and on the other hand, make the development of enterprises to form a benign effect. At the same time, we need to focus on building a reverse supply chain for automotive battery recycling. Through the recovery of power batteries to achieve reuse, reduce their own business operating costs.

The new energy automobile industry can realize the optimization of supply chain decision-making by building a smart logistics platform, which can timely and accurately monitor the inventory status of the enterprise, greatly reduce the inventory cost of the enterprise, and realize the optimization and upgrading of the supply chain decision-making of the new energy automobile industry.

IV. C. Downstream marketing and branding

The first is to build a network sales platform. With the combination of online and offline marketing methods, we will broaden the sales channels of our products and provide consumers with a better car-buying experience. The second is to improve the level of sales and service, and continue to optimize the pre-sales, sales and after-sales service. In terms of brand building, new energy vehicle manufacturers need to increase publicity efforts to shape the brand image, shaping the brand image by continuing to deliver corporate values to consumers and continuously improve product quality, and further enhance the brand value by expanding the high-end product line.

V. Conclusion

The multi-objective chaotic optimization algorithm performs well in new energy vehicle supply chain pricing. Simulation data based on 145,800 potential consumers of Enterprise A in 2022 showed that the method resulted in total sales of 51,796 new energy vehicles with an average vehicle price of 258,900 yuan. The overall error mean of the simulation model is only 3.39%, proving that the model stability is good. After optimization, the price of middle and low-priced models increases as a whole, the price change of high-priced models is not obvious, and the price of all models finally stabilizes in the range of 250,000-400,000 yuan.

The centralized decision-making model is better than the decentralized decision-making model. Numerical simulation results prove that centralized decision-making achieves Pareto improvement, and the price range of centralized decision-making is 229,500-250,000 yuan, which is significantly lower than the price range of decentralized decision-making under the same demand conditions. Profit distribution through the Shapley value method can realize a win-win situation for multiple parties in the supply chain and effectively solve the problem of coordination of interests between manufacturers and dealers.

It is suggested that new energy automobile enterprises should optimize all aspects of the supply chain: the upstream should conduct extensive market research, improve product inspection standards, and promote technological innovation through battery self-research and technical cooperation; the midstream should focus on green production, build a reverse supply chain for automobile battery recycling, and build a smart logistics platform to accurately monitor the inventory status; and the downstream should build a network sales platform, improve the level of sales service, and increase the strength of brand publicity. The downstream should build a network sales platform, improve sales and service level, and increase brand publicity. These measures will help new energy automobile enterprises to build a more efficient and coordinated supply chain system and maintain the momentum of sustainable development in the fierce market competition.

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