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Optimization Analysis of Smart Energy Systems in the Fresh Supply Chain Based on Differential Games

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Abstract. The energy issue has gradually become a major focus of strategic competition among major nations in the contemporary world. Achieving a balance between energy, cost, and ecology is crucial, particularly in specific contexts. As one of the critical factors influencing global climate, carbon emissions have consistently been a green indicator of concern for countries worldwide. This paper addresses optimizing energy costs in the cold chain transportation of the fresh supply chain to obtain a model with low carbon emissions and transportation costs. Initially, the paper explores the equilibrium between energy and cost optimization using the theoretical framework of differential games in game theory. Building upon this, an intelligent energy system is proposed, and a basic model for constructing a smart grid is provided based on commonly used electric power. Using this as the foundational concept, a game model is constructed, considering the conflicting objectives of cost minimization, time efficiency, and energy conservation in addressing the primary issue of energy savings in the fresh supply chain, specifically the transportation path optimization problem. Compared to traditional models, the model presented in this paper reduces the scheduling of two refrigerated trucks. By optimizing this model, the transportation path's length is shortened by 5.50%, the carbon emission is decreased by 8.9%, and the model's overall cost is reduced by 4.94%. This study presents a game model that may efficiently optimize the fresh product transportation chain, reducing carbon emissions and expenses. The model has certain practical applications and serves as a guide.

Key words. Smart Energy Systems, Carbon Emissions, Zero-Sum Game, Fresh Supply Chain, Transportation Optimization.

1. Introduction

In the contemporary global landscape, issues about energy and ecology have become focal points in the geopolitical arena. Striking a balance between energy consumption, costs, and ecological considerations is particularly pronounced in specific applications, such as cold chain logistics in the fresh food supply chain, representing a problem involving the equilibrium of energy consumption, costs, and ecological impact [1]. Carbon emissions are a major contributor to the global climate and have long been a green statistic of concern for governments worldwide [2]. To maintain the quality of cold chain logistics, regulating the uniqueness of its products and strict transportation standards are considerable obstacles. To ensure the final rate and yield of the product, it is necessary to adhere to quality assurance at every interface and connection point. Cold chain logistics is a supply chain system with high input, high energy consumption and impact on the environment. Optimization of its distribution route can effectively reduce the overall carbon emission of the system and meet the requirements of sustainable development [3]. Huang et al. [4] argue that in transportation, the resources invested by production and processing enterprises are relatively minimal, and studying the degree of resource input in the supply chain process holds significant implications for the safety of fresh agricultural products. Green logistics was proposed by [5] C. Bao, and S. Zhang [5], who converted transport-related carbon emissions into expenses and included them in the objective function. To reduce the total cost, they studied the joint distribution route optimization problem and used an enhanced genetic algorithm to solve it. F. S. Fan et al. [6] established a game optimization model, and the model took total cost as the objective function, and the enhanced ant colony algorithm solved the problem. Y. Li et al. [7] combined low-carbon environmental protection with enhanced particle swarm optimization technology to establish a cold chain transportation route optimization model for fresh agricultural products. When studying the cooperative and non-cooperative models between two countries with transboundary CO2 pollution, L. Bertinelli [8] used the differential game method to conclude that the feedback strategy can reduce CO2 emissions and thus improve environmental performance. J. Hong, and H. Pei [9] built a supply chain model composed of a supplier and a manufacturer, studied the dynamic coordination of quality control by using the differential game model, and finally concluded that the Nash equilibrium solution of cooperative quality control among supply chain members is better than the non-cooperative Nash equilibrium solution. M. Zhou, and J. Lin [10] used a differential game to study the dynamic impact of alliances among supply chain members on advertising investment. They found that alliance behavior between manufacturers and retailers would encourage supply chain members to invest in advertising. D. Q. Ma, and J. S. Hu [11] studied the closed-loop supply chain by introducing member fairness concern behavior and using the differential game to obtain the dynamic equilibrium solution of closed-loop supply chain members. Cheng Shu-su et al. [12] Chestablished a three-tier green supply chain composed of manufacturers, retailers, and consumers, studied the dynamic change of product green innovation level based on the differential game method, and introduced dynamic wholesale price contract to coordinate supply chain profits according to the equilibrium solution under centralized and decentralized decision-making, to promote cooperation among supply chain members. G. Zhu, and D. You [13] used differential game theory to build a time change model of product green level affected by market demand. They analyzed the optimal pricing level under wholesale and revenue-sharing contracts and compared it with centralized decision-making.

In summary, scholars have mainly focused on setting objective functions based on the research subject and designing corresponding algorithms to solve the optimization problem of cold chain logistics vehicle routes. There needs to be more consideration from an energy perspective that comprehensively integrates costs and ecology in optimizing the fresh food supply chain. This paper introduces a groundbreaking application of game theory in the energy field, proposing a smart energy system. Considering the ubiquity of electrical energy, a specific intelligent grid architecture is presented. Building on this conceptual foundation, a game model is constructed to address the primary energy-saving issue in the fresh food supply chain, namely, the optimization of transportation routes through game optimization. This paper presents a differential game-based game optimization model that can effectively make the fresh supply chain low-carbon and economical. This suggests that the model and RL algorithm in this paper can be better applied in the fresh supply chain optimization design research to achieve the goal of transporting high-quality fresh products at a low cost and low carbon.

2. Smart Energy System based on Differential Game Theory

A. Zero Sum Differential Game

In the contemporary world, the rapid development of the technological revolution has prompted scientists and engineers in various industries and fields to grasp and transform the world urgently. In the backdrop of such an era, Differential Game Theory has emerged. The theory of differential games addresses the strategic interactive problems among multiple game participants (decision-makers). These participants are commonly referred to as players or agents. In a specific game scenario, each player makes optimal choices from multiple interactive strategies that align with their interests, thereby achieving extremum (maximization or minimization) of their objective function (utility or loss) [14].

The game theory employed in this paper is a zero-sum game, specifically a two-player zero-sum game. In simpler terms, it is a zero-sum game between energy conservation and transportation efficiency. Recently, Multi-Agent Reinforcement Learning (MARL) has been developed with a focus on this game [15], [16], [17]. When dealing with a game like this, the goal of the MARL agent is to minimize worst-case performance - that is, vulnerability to attack by all possible opponents. As a traditional solution concept in game theory [19], [20], Nash equilibrium (NE) [18] is reached when the availability of both agents is close to zero. Although this goal is simple, it takes a lot of workforces to design the algorithm to optimize it. Iteration is an effective strategy [19]. In iterative techniques, participants expand the pool of agents. A new agent is taught and added to the player's strategy library in each iteration. However, in an automated course, it becomes difficult to create effective updating rules for "who to compete against" (e.g., opponent selection) and strategies for "how to beat them" (e.g., determining the best response). The challenge becomes more complex when other requirements are considered, including producing organisms with behavioral diversity [22], [23] or the ability to generalize. Below, the author will provide some appropriate definitions for the problems mentioned in this paper.

Let Θ be a universal set, R an equivalence relation on Θ, Ω a non-empty subset of Θ, and $[\theta]_{\mathrm{R}}$ the equivalence class set of R. Equation (1) defines the upper and lower approximations of the set Ω.

$$\overline{\mathrm{R}\Omega} = \{\theta \in \Theta : [\theta]_R \cap \Omega \neq \varphi\}$$
$$\underline{\mathrm{R}\Omega} = \{\theta \in \Theta : [\theta]_R \subseteq \Omega\} \tag{1}$$

$\aleph\Omega$ is $\overline{\mathrm{R}\Omega}$ minus $\underline{\mathrm{R}\Omega}$. If the set $\aleph\Omega$ is non-empty, then the set Ω is referred to as a rough set. A rough set ($\overline{\mathrm{R}\Omega},\underline{\mathrm{R}\Omega}$) is the set of all sets that have the same upper and lower approximations.

If π is a non-negative real-valued additive set function, Λ is a σ-algebra on Ω, and θ is an element in Λ, then $(\Omega,\theta,\Lambda,\pi)(\Omega,\theta,\Lambda,\pi)$ is called a rough space.

A function from the rough space $(\Omega,\theta,\Lambda,\pi)(\Omega,\theta,\Lambda,\pi)$ to the real number set is called a rough variable (ξ^R). Assume that every real number fulfilling equations (2) and (3) is $\xi^{-(\mathrm{LAI})-(\mathrm{LAI})}, \xi^{+(\mathrm{LAI})+(\mathrm{LAI})}, \xi^{-(\mathrm{UAI})-(\mathrm{UAI})}$ and $\xi^{+(\mathrm{UAI})+(\mathrm{UAI})}$.

$$\xi^{-(\mathrm{UAI})} \leq \xi^{-(\mathrm{LAI})} \leq \xi^{+(\mathrm{LAI})} \leq \xi^{+(\mathrm{UAI})} \tag{2}$$

$$\xi^R = \left[\left(\xi^{-(\mathrm{LAI})}, \xi^{+(\mathrm{LAI})}\right) : \left(\xi^{-(\mathrm{UAI})}, \xi^{+(\mathrm{UAI})}\right)\right] \tag{3}$$

If equation (4) is satisfied, then it can be termed as a rough variable.

$$\begin{cases} \xi^{-(\mathrm{LAI})} \le \xi^{R}(\theta) \le \xi^{+(\mathrm{LAI})}, \theta \in \mathrm{R}\Omega \\ \xi^{-(\mathrm{UAI})} \le \xi^{R}(\theta) \le \xi^{-(\mathrm{LAI})} \text{or} \xi^{+(\mathrm{LAI})} \le \xi^{R}(\theta) \le \xi^{+(\mathrm{UAI})}, \theta \in \aleph\Omega \end{cases} \quad (4)$$

Let Tr represent an approximate space measure. Equation (5) illustrates how a measure Tr is defined on a set $\mathrm{A} \in \Lambda$. Equation (6) defines the trust measure of the rough value, assuming ξ^R is a rough variable.

$$\mathrm{T}r\{\mathrm{A}\} = \frac{1}{2}\left(\overline{Tr}\{\mathrm{A}\} + Tr\{\mathrm{A}\}\right) \quad (5)$$

where

$$\overline{\mathrm{Tr}}\{\mathrm{A}\} = \frac{\pi\{\mathrm{A}\}}{\pi\{\Omega\}}, \quad Tr\{\mathrm{A}\} = \frac{\pi\{\mathrm{A} \cap \theta\}}{\pi\{\theta\}}$$

$$\mathrm{Tr}\left\{\xi^R \le \beta\right\} = \begin{cases} 0, & \text{if } \beta \le \xi^{-(\mathrm{UAI})} \\ \frac{1}{2}\left(\frac{\xi^{-(\mathrm{UAI})} - \beta}{\xi^{-(\mathrm{UAI})} - \xi^{+(\mathrm{UAI})}}\right), & \text{if } \xi^{-(\mathrm{UAI})} \le \beta \le \xi^{-(\mathrm{LAI})} \\ \frac{1}{2}\left(\frac{\xi^{-(\mathrm{UAI})} - \beta}{\xi^{-(\mathrm{UAI})} - \xi^{+(\mathrm{UAI})}} + \frac{\xi^{-(\mathrm{LAI})} - \beta}{\xi^{-(\mathrm{LAI})} - \xi^{+(\mathrm{LAI})}}\right), & \text{if } \xi^{-(\mathrm{LAI})} \le \beta \le \xi^{+(\mathrm{LAI})} \\ \frac{1}{2}\left(\frac{\xi^{-(\mathrm{UAI})} - \beta}{\xi^{-(\mathrm{UAI})} - \xi^{+(\mathrm{UAI})}} + 1\right), & \text{if } \xi^{+(\mathrm{LAI})} \le \beta \le \xi^{+(\mathrm{UAI})} \\ 1, & \text{if } \beta \ge \xi^{+(\mathrm{UAI})} \end{cases}$$

(6)

Additio ally, the α -pessimistic value of ξ^R is computed
n
as shown in equation (7).

$$\xi^R_{\inf}(\alpha) = \inf\left\{\beta : \mathrm{Tr}\left\{\xi^R \le \beta\right\} \ge \alpha\right\}$$

$$= \begin{cases} (1-2\alpha)\xi^{-(\mathrm{UAI})} + 2\alpha\xi^{+(\mathrm{UAI})}, \text{if } \alpha \le \frac{\xi^{-(\mathrm{LAI})} - \xi^{-(\mathrm{UAI})}}{2\left(\xi^{+(\mathrm{UAI})} - \xi^{-(\mathrm{UAI})}\right)} \\ 2(1-\alpha)\xi^{-(\mathrm{UAI})} + (2\alpha-1)\xi^{+(\mathrm{UAI})}, \text{if } \alpha \ge \frac{\xi^{+(\mathrm{LAI})} + \xi^{+(\mathrm{UAI})} - 2\xi^{-(\mathrm{UAI})}}{2\left(\xi^{+(\mathrm{UAI})} - \xi^{-(\mathrm{UAI})}\right)} \\ \frac{\xi^{-(\mathrm{UAI})}\left(\xi^{+(\mathrm{LAI})} - \xi^{-(\mathrm{LAI})}\right) + \xi^{-(\mathrm{LAI})}\left(\xi^{+(\mathrm{UAI})} - \xi^{-(\mathrm{UAI})}\right) + 2\alpha\left(\xi^{+(\mathrm{LAI})} - \xi^{-(\mathrm{LAI})}\right)\left(\xi^{+(\mathrm{UAI})} - \xi^{-(\mathrm{UAI})}\right)}{\left(\xi^{+(\mathrm{LAI})} - \xi^{-(\mathrm{LAI})}\right) + \left(\xi^{+(\mathrm{UAI})} - \xi^{-(\mathrm{UAI})}\right)}, \text{otherwise} \end{cases}$$

(7)

Furthermore, the expected value of ξ^R is defined as in equation (8).

$$E\left[\xi^R\right] = \int_0^{\infty} \mathrm{Tr}\left\{\xi^R \ge \mathrm{x}\right\} dx - \int_{-\infty}^{0} \mathrm{Tr}\left\{\xi^R \le \mathrm{x}\right\} dx \quad (8)$$

Based on the series of definitions and computational expressions, the expected value of ξ^R is given by:

$$\mathrm{E}\left(\xi^R\right) = \frac{1}{2}\left[\mu\left(\xi^{-(\mathrm{LAI})} + \xi^{+(\mathrm{LAI})}\right) + (1-\mu)\left(\xi^{-(\mathrm{UAI})} + \xi^{+(\mathrm{UAI})}\right)\right] \quad (9)$$

If μ in the equation is 0.5, then:

$$\mathrm{E}\left(\xi^R\right) = \frac{1}{4}\left[\xi^{-(\mathrm{LAI})} + \xi^{+(\mathrm{LAI})} + \xi^{-(\mathrm{UAI})} + \xi^{+(\mathrm{UAI})}\right] \quad (10)$$

Through the aforementioned series of definitions, the game min-max can be represented as follows.:

$$\min_{v} \max_{w} L\left(v(t), w(t)\right) = \phi\left(y\left(t_f\right)\right) + \int_{t_0}^{t_f} G\left(y(t), v(t), w(t), t\right) dt,$$

Subject to

$$y(t) = \mathrm{M}\left(y(t), v(t), w(t), t\right),$$

$$y(t_0) = y_0, t \in \left[t_0, t_f\right], n \quad (11)$$

The next task is to finish the game. Although linear programming can solve a two-person zero-sum game's Nash equilibrium (NE) in polynomial time, it is a very limited method. For example, when the action space is too large or continuous, it is impossible to use LP. Instead, additional approximation techniques are needed, such as virtual games (FP), distributed Oracle (DO), or PSRO methods. The agent is iteratively trained and introduced into the player's strategy pool in these methods, taking advantage of the previous aggregation strategies (e.g., FP with a time average strategy and DO/PSRO with a subgame NE), which utilize iterative optimal response dynamics. The modified NE algorithm, the no-regrets algorithm, and alpha-rank are other solving principles included in this broad iterative framework. In this work, we do not rely on any prior knowledge of game theory but instead employ meta-learning techniques to discover concepts of effective solutions from the interactions of the environment.

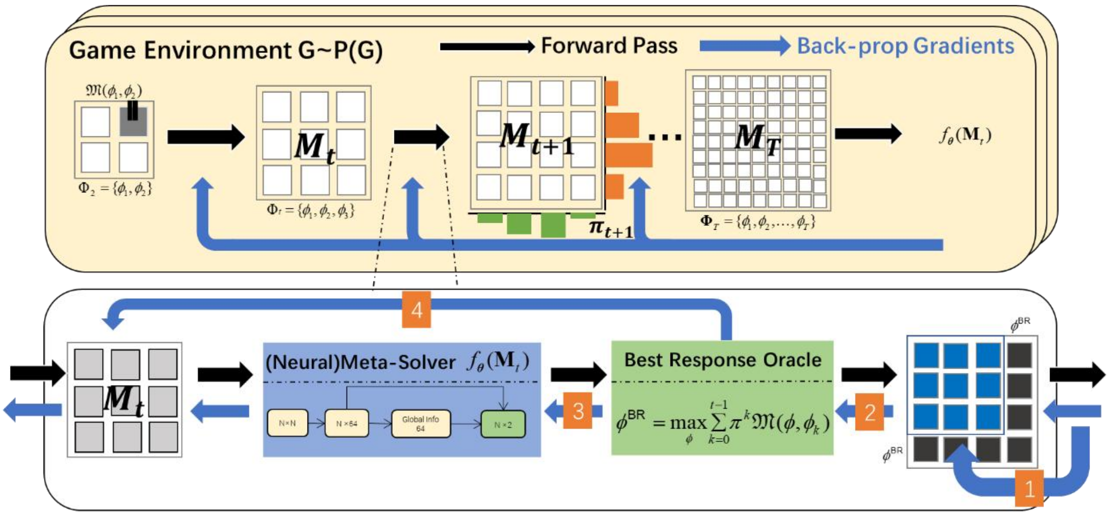

Fig.1 RL Algorithm Flowchart

Because it may improve sample efficiency in tasks like categorization, regression, and reinforcement learning, meta-learning is gaining popularity. It can swiftly adapt to new jobs thanks to its ability to discern between different learning processes. PROMP checks for meta-gradient bias and performs a mathematical evaluation of the MAML-RL formula. ES-MAML uses evolutionary techniques to optimize gradient-free, avoiding the Hessian estimation problem. The meta-learning issue is a second RL process with "slow" parameter updates in RL2 and L2RL. Components of meta-learning reinforcement learning algorithms, such as bootstrapping, goal functions for value/policy networks, intrinsic incentives, discount factors, auxiliary tasks, and deviation from policy update objectives, have been used more often in recent times. The secret of their success was to use gradient descent on a gradient descent update sequence generated by selecting the objective function, an approach known as meta-gradient. Figure 1 shows the generalization ability of a meta-learning reinforcement learning algorithm when dealing with different problems. In addition to meta-gradients, evolutionary strategies (ES) have also been effectively applied. Our research, on the other hand, aims to achieve the same goal as these previous approaches: to find MARL algorithms that efficiently solve different types of two-person zero-sum games and to demonstrate that these algorithms can be applied to other kinds of games.

Only some attempts have been made to use meta-learning in multi-agent contexts thus far. To train a credit assignment module for more effective value network deconstruction, MNMPG uses meta-gradients. A non-stationary meta-gradient solution for continuous adaptation in dynamic situations is what we call Meta-PG. Using an opponent modeling method known as LOLA, which considers opponent learning processes and environmental non-stationarity, Meta-MAPG expands Meta-PG to a multi-agent situation.

B. Energy and Differential Games

Energy is an essential foundation supporting the development of human society, but energy consumption has seriously impacted the environment and resources [26]. Therefore, energy conservation has become an important global issue for sustainable development. Differential games, as a branch of game theory, study the strategic choices and optimal decisions of participants in games. This section will explore the relationship between energy conservation and differential games and analyze the application of differential games in energy conservation decision-making.

Differential games are a method for studying dynamic games, investigating the strategic choices and optimal decisions of participants over continuous time. The discussion in this paper will primarily focus on the game of resource consumption and carbon emissions using electricity resources.

Electricity resources mainly come from coal, natural gas, nuclear energy, and renewable energy, and there is a game relationship between the consumption of these resources and carbon emissions. Sun Hongbin believes that energy Internet is a typical application of "Internet + smart energy" [27]. Wang Zhongmin proposed that the smart energy industry has developed into the energy Internet after long-term accumulation [28]. Wang Yongzhen pointed out that the development of smart energy can promote the extensive and highly integrated energy flow and information flow, and will become a key link in the entropy increase and decrease rate of the advanced form of integrated energy system (energy Internet) at the present and future stages [29]. Firstly, the consumption of electricity resources leads to many carbon emissions. The combustion of fossil fuels such as coal and natural gas releases a significant amount of carbon dioxide and other greenhouse gases, adversely affecting global climate change. Therefore, using these resources for electricity generation exacerbates the issue of carbon emissions. Secondly, carbon emissions also restrict the consumption of electricity resources. With the increasing global concern for climate change, many countries and regions have implemented carbon emission restrictions and reduction targets, imposing stricter requirements on the use of fossil fuels. This has placed greater pressure and challenges on the electricity industry in balancing resource consumption and carbon emissions.

In a variety of commonly used energy, electric energy can be said to be used every moment, and the use of electric energy can not be separated from the infrastructure construction of the power grid; the power grid is the energy pillar of the city, responsible for the energy from the power plant to the hands of consumers safely and reliably, for a variety of interconnected services to provide electricity and heat. However, conventional power grids could have technological issues, including shortcomings in control systems, one-way protection, and communication infrastructure. To handle dispersed generation and rising demand, traditional power systems could need assistance. As a result, academic research on grid construction often focuses on maximising the utilization of existing grid infrastructure while reducing investment costs. The smart grid proposed in this paper can be built on the smart city model. The so-called smart grid is the organic combination of the unique technology of the information age and the original infrastructure after the rapid development of today's science and technology. It is mainly about collecting and using various data, such as energy generation, the mode of transportation followed and cost. The capacity to satisfy increasing consumer load needs without additional infrastructure, self-healing capabilities, microgrid power exchange, and independent operation are some of the key elements of the smart grid outlined. The difference between a smart grid and a traditional power grid is its informatization, which uses advanced sensors, communication technologies and intelligent algorithms to integrate and collect data on existing power grid infrastructure and, based on this, improve energy efficiency [30], [31]. The author's Figure 2 shows the smart grid's basic layout integrated with the information age's latest technological products. As mentioned above, using advanced sensors to monitor and collect relevant data in the power grid is the most important thing to form a smart grid. Through these advanced sensors, we can monitor the use of users in different time and space in the grid to obtain real-time data on electricity consumption and generation. Utility firms get this data and can use it to make choices about the production and distribution of electricity. Phasor measuring units (PMUs), fault current sensors, temperature sensors, voltage sensors, current transformers (CTs), power quality sensors, gas sensors, pressure sensors, humidity sensors, etc., are among the sensors that are often employed in smart grids.

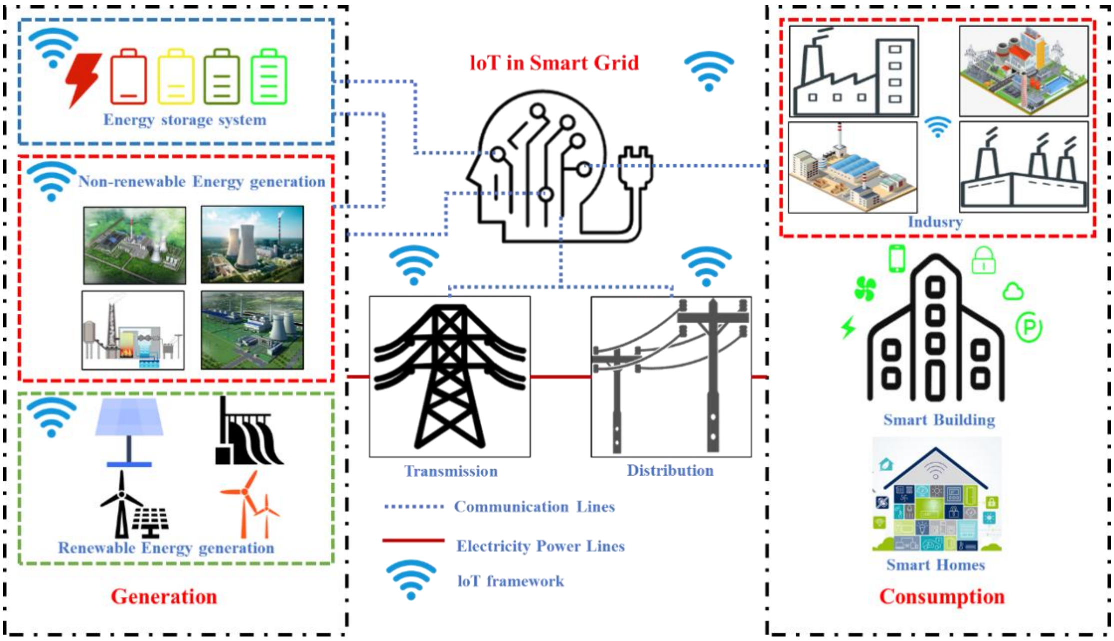

Fig.2 Layout of Smart Grid Using the Latest Technology

In the information age, we can use communication technologies such as 5G networks and Wi-Fi for data transmission to establish connections between different components in the smart grid. This helps us monitor individual users' usage in the grid, as mentioned earlier. Power outages may be prevented, energy waste can be reduced, and energy distribution can be managed using this information. One of the main advantages of a smart grid is its ability to integrate renewable energy sources more easily. The production of renewable energy sources, such as solar and wind power, may be tracked by modern sensors, which can also provide the most recent availability information. This makes it possible for utilities to adjust how energy is produced and distributed to consider fluctuations in the supply of renewable energy. There is a game-like correlation between the utilization of electrical resources and carbon emissions.

On the one hand, the electricity industry needs to meet energy demand and provide a stable power supply; on the other, it also needs to reduce carbon emissions and minimize environmental impact. In this scenario, the electricity industry must continuously explore and promote clean energy, improve energy efficiency, reduce carbon emissions, and balance resource consumption and environmental protection. At the same time, governments, businesses, and society need to work together to establish more stringent environmental policies and regulations, promoting the development of the electricity industry in a low-carbon, clean direction.

C. Smart Energy System

Zhao Yu from Intel China's IoT Business Unit proposed that smart energy refers to the entire energy-related and usage information and communication technology (ICT) activities, from the initial development and production of energy to its final consumption. Technology-driven integration, optimization, interaction, etc., achieve the scheduling and operation of an energy system within a regional framework, optimizing energy management and usage. The Pricewaterhousecoopers China Research Center's Lu Lingli, a smart energy researcher, explained that the "smart" + "Energy" management system leverages information technology to harness renewable energy sources like solar and wind power.This is aimed at achieving energy conservation and emission reduction for human society. Subsequently, energy information is collected throughInternett information technology, providing an interconnected, open, and shared resource platform within the entire energy industry, including solutions for remote control and collaborative management. The "China Smart Energy Industry Development Report (2015)" proposes that smart energy must apply the Internet and modern communication technology to real-time monitoring, analysis, and optimization of energy production, usage, scheduling, and efficiency conditions. It should be based on real-time detection, reporting, and optimization processing on big data and cloud computing foundations to achieve an open, transparent, decentralized, and widely voluntary participating comprehensive energy management system. Lin Boqiang from Xiamen University's Energy Economics and Collaborative Innovation Center suggests that smart energy's "smart" aspect primarily lies in the interaction between the supply and consumption sides. This is the core of smart energy, reflecting a gradual shift from passive acceptance to active consumer participation in energy consumption. Smart energy also involves technological progress ref, forms, and innovations in mechanisms and systems. Yu Qing, a special researcher at the China Energy Youth Forum, proposes that the core of smart energy lies in the deep integration of informatization and automation. It provides intelligent services to energy suppliers, such as power and grid companies, while offering better energy service solutions for consumers on the demand side.

Smart energy combines various emerging technologies, including big data and IoT technology, digital communication technology, comprehensive energy coordination technology, distributed energy technology, and the latest technologies related to supply, transmission, and storage in the energy industry. Additionally, it incorporates excellent decision-making system technology. With the current high-speed bidirectional communication network technology as its foundation, it spans the entire energy industry from production to final consumption, ultimately achieving coordinated interconnection and continuous optimization of overall decisions in the energy industry for reliable, safe, environmentally friendly, and economically supportive sustainable development. Some experts and scholars focus more on its commercial characteristics when defining smart energy. With "intelligence" as the core, it seeks to develop a brain-like energy system using human intelligence. This system is capable of self-organization, self-detection, self-optimization, and self-maintenance. It is then applied as a service and application, driving optimization operations in all aspects and actively promoting technological and institutional innovations in the energy industry. The ultimate goal is to achieve a reliable, safe, environmentally friendly, and economically supportive new form of energy.

Although the perspectives and emphases of the above two viewpoints differ, their conclusions are consistent. The value of the smart energy system lies in providing a reliable, safe, environmentally friendly, efficient, and stable comprehensive energy service for the country, cities, and people.

The definition and key points of the smart energy proposed in this paper are as follows. Firstly, in terms of energy form, smart energy is still based on traditional energy, gradually transitioning towards clean and new energy sources.

Secondly, regarding the main features, smart energy is based on "intelligence." Its "intelligence" manifests in various forms, incorporating human intelligence to build a humanoid intelligent system. This system can self-update, self-optimize, self-detect, and self-maintain. It demonstrates continuous industrial innovation and upgrades, as well as ongoing reforms and optimizations in various links and systems.

Thirdly, regarding manifestation, a crucial point is integration or fusion. Whether in terms of technology, it integrates emerging technologies from multiple fields, applied in various links from energy production to consumption, such as the energy storage system shown in Figure 3. It also involves deep integration in multiple dimensions, such as integrating technology, concepts, services, innovation, and more. It is the profound combination of technological modes and commercial operations.

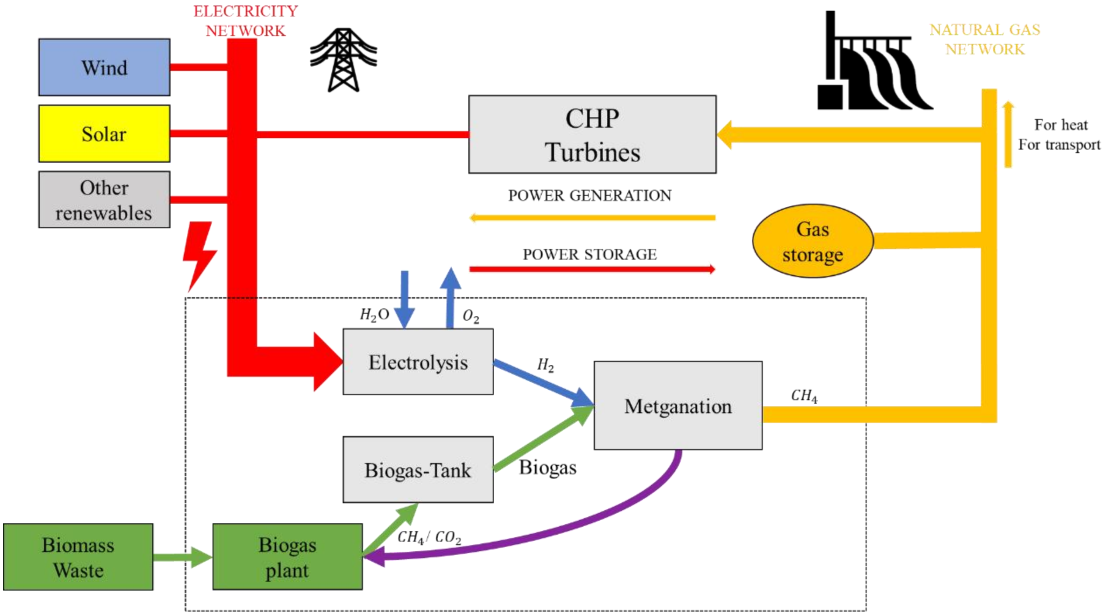

Fig.3 Schematic Diagram of Energy Storage System

Lastly, in terms of purpose, everything proposed has a purpose. Without a purpose, none of the previous points would be valid. Smart energy aims to obtain an environmentally friendly, efficient, and stable comprehensive smart energy system for sustainability principles. It ultimately serves the development of every individual, the entire country, and even the entire human race.

3. Optimization of Energy Conservation in the Fresh Produce Supply Chain: A Game-Theoretic Approach

Fresh agricultural products are a category within the larger classification of agricultural products. Generally, agricultural products can be categorized into perishable and non-perishable, with perishable agricultural products referred to as fresh agricultural products. Freshness is an important indicator of the value of such agricultural products, characterized by perishability and strong timeliness. Vegetables, fruits, aquatic products, poultry, eggs, meat, and dairy products are common examples of fresh agricultural products in our daily lives, broadly categorized into fruits and vegetables, meat, and seafood. People's demands for the quality and freshness of agricultural goods are rising as a result of economic growth and people's ever-growing quest for a better living. Fresh agricultural products have become an indispensable part of our daily lives. However, unlike other consumer goods, fresh agricultural products are perishable and time-sensitive, easily affected by external environmental conditions. The perishable and highly time-sensitive characteristics pose significant challenges to the quality assurance of fresh agricultural products, resulting in severe losses and economic losses yearly. How to reduce losses, promote the development of related industries, and increase farmers' income has become a research hotspot.

Currently, the main entities in the supply chain include suppliers, manufacturers, distributors, retailers, and users, with complex and interrelated relationships. The simple production chain has transformed into a value chain, expanding from within the enterprise to a globally integrated supply chain. The supply chain has evolved from a simple chain to a complex network. In modern economic activities, most supply chains do not exist independently, but rather, multiple interrelated supply chains collectively form a vast and complex supply chain network. With the continuous modernization of the economy and the continuous innovation of the value chain, the refinement of production cooperation and innovation in production and sales models, the complexity of the supply chain network has increased. A complex supply chain network has evolved from the original chain-shaped supply chain, causing the flow of products, information, funds, value, knowledge, control, and decision-making in the supply chain to be exponentially more complex than a regular supply chain. These factors are intricately intertwined, making the current supply chain network face significant challenges in cooperation, optimization, and risk control.

Additionally, in a complex supply chain network, nodes are influenced by nodes on the same supply chain and nodes on different supply chains. Any subtle changes in a node will greatly impact the entire supply chain network. Therefore, the organizational structure, topology, and nature of the supply chain network will directly affect the formation, operation, and changes.

The fresh supply chain is a complex network with multiple stakeholders and activities, such as producers, distributors, retailers, and consumers. Efficient transportation of fresh products is crucial to ensuring their quality and safety while minimizing energy consumption and environmental impact. In this section, the paper will propose a smart energy system and strategic interactions among different participants in the fresh supply chain to optimize transportation routes and increase the utilization of renewable energy for energy savings. By considering the conflicting goals of cost minimization, time efficiency, and energy savings, the paper aims to propose a game theory framework and conduct optimization calculations.

The flowchart of the optimization analysis process in this paper is shown in Figure 4.

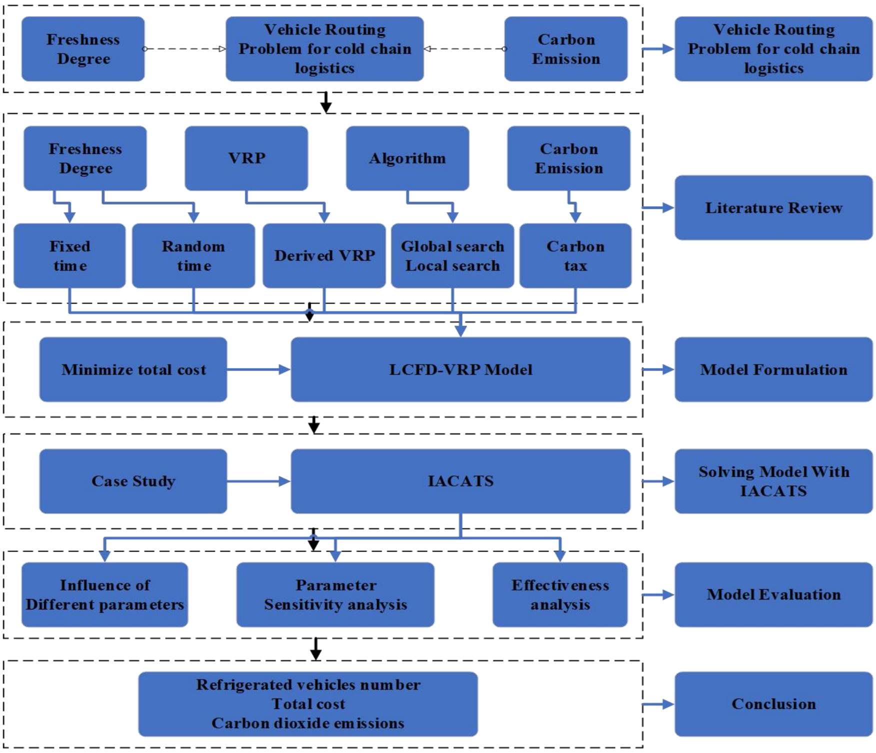

Fig.4. Optimization Analysis Flowchart in this Paper

A. Fresh Supply Chain Route Optimization

The cold chain logistics challenge is a major one for the fresh supply chain, and this research focuses on one optimization path in particular—route optimization. The following is a simple summary of the issue: Many customers can be served by a market for fresh raw materials. Cold chain logistics trucks must stop at each customer's site, begin at the raw material market, and finish by returning to it. They are screened using the same transport vehicle capacity as the industry standard. Each consumer's geographic coordinates and the required commodities' coordinates are known, and one vehicle may deliver the necessary goods. Apart from those above, it is imperative to restrict the operating hours of cold chain logistics trucks. The truck departs the market for new raw materials at time zero. Fresh agricultural products typically lose some freshness during the docking and delivery process to customers. This is because product freshness is initially set at 100%, which can lead to consumer dissatisfaction with the distribution and additional expenses. In summary, the development process of the game model and consumer fundamental needs dictate that we must consider the cost of carbon emissions, the previously mentioned penalty costs, the maximum working duration and load of cold chain logistics trucks, and so on. This route optimization aims to provide hard-chain transportation that is inexpensive, low-carbon, and efficient.

All members of the supply chain reach an agreement to make decisions according to the principle of overall profit maximization. The superscript C represents the decision-making mode, so the decision-making problem is as follows:

$$\max_{\varpi,M,p} J_M^{C1} = \int_0^\infty e^{-\rho t}[\varpi\delta E(a-bp) - \frac{\eta_M}{2}M^2]dt$$
$$\max_{p,\varpi,R} J_R^{C1} = \int_0^\infty e^{-\rho t}[(p-\varpi)\delta E(a-bp) - \frac{\eta_R}{2}R^2]dt \tag{12}$$

Under the decentralized decision-making mode, the optimal preservation effort balance strategy of manufacturers and retailers is as follows:

$$M^{C1*} = \frac{\alpha a^2\delta}{8b\eta_M(\rho+\theta)} \quad ,R^{C1*} = \frac{\beta a^2\delta}{16b\eta_R(\rho+\theta)} \tag{13}$$

Under the decentralized decision-making model, the long-term profits of the manufacturer, retailer and the whole supply chain are as follows:

$$J_M^{C1}=\frac{a^2\delta}{8b(\rho+\theta)}E_0+\frac{a^4\delta^2}{128b^2\rho(\rho+\theta)^2}(\frac{\alpha^2}{\eta_M}+\frac{\beta^2}{\eta_R})$$
$$J_R^{C1}=\frac{a^2\delta}{16b(\rho+\theta)}E_0+\frac{a^4\delta^2}{128b^2\rho(\rho+\theta)^2}(\frac{\alpha^2}{\eta_M}+\frac{\beta^2}{4\eta_R})$$
$$J_C^{C1}=\frac{3a^2\delta}{16b(\rho+\theta)}E_0+\frac{a^4\delta^2}{128b^2\rho(\rho+\theta)^2}(\frac{2\alpha^2}{\eta_M}+\frac{5\beta^2}{4\eta_R})$$

(14)

Based on the considerations described in Section 2 of this paper, the LCFD-VRP model for cold chain path optimization can be formulated as Equation (15):

$$\min C=\frac{C_1+C_2+C_3+C_4+C_5}{\sum_{i=0}^{N}\theta_i} \tag{15}$$

which is subject to：

$$\sum_{i=1}^{n}x_{0i}^k\le 1,\forall k\in\overline{K} \tag{16}$$

$$\sum_{k=1}^{K}\sum_{j1}^{n+1}x_{ij}^k=1,\forall i\in N' \tag{17}$$

$$\sum_{i=0}^{n}\sum_{i=1}^{n}x_{ij}^k q_j\le Q,\forall k\in\overline{K} \tag{18}$$

$$\mathbf{U}_j^k=\sum_{k=1}^{K}\sum_{i=1}^{n}\left(\mathbf{U}_i^k-\mathbf{q}_i\right)\mathbf{x}_{ij}^k,\nabla j\in\mathbf{N}^- \tag{19}$$

$$\sum_{k=1}^{k}\sum_{i=1}^{n}x_{i(n+1)}^k\left(\mathrm{U}_i^k-\mathrm{q}_i\right)=0 \tag{20}$$

$$\tau_j=\sum_{k=1}^{k}\sum_{i=0}^{n}x_{ij}^k\left(S_i+d_{ij}/v+\max\{G_i\}\right)\quad,\forall j\in N$$

$$\sum_{i=1}^{n}\left([\max\{\mathrm{S},\mathbf{x}_j\}+\mathrm{S}_i+d_{i(n+1)}/v)x_{i(n+1)}^k\le 200\right. \tag{21}$$

$$\forall k\in\overline{K}$$

$$\tau_i\le\overline{I_i},\forall i\in N \tag{22}$$

$$x_{ij}^k\in\{0,1\},\forall i,j\in N,\forall k\in\overline{K} \tag{23}$$

Equation (15) is an objective function, which includes the various costs mentioned above, and its objective is to minimize the total distribution cost. Equations (16) and (17) indicate that each consumer needs only one logistics vehicle service, and the vehicle can only stop at the consumer at this time. Equations (18)-(20) represent the constraints on the total transportable volume of logistics vehicles. According to Equation (19), when the car has stopped k times for the consumer, the total amount must be subtracted from the goods unloaded in the previous k times. Equation (20) indicates that each logistics vehicle transports no more or less goods, just enough to serve every expected consumer. Equations (21)- (23) represent time constraints. The approximate diagram is shown in Figure 5.

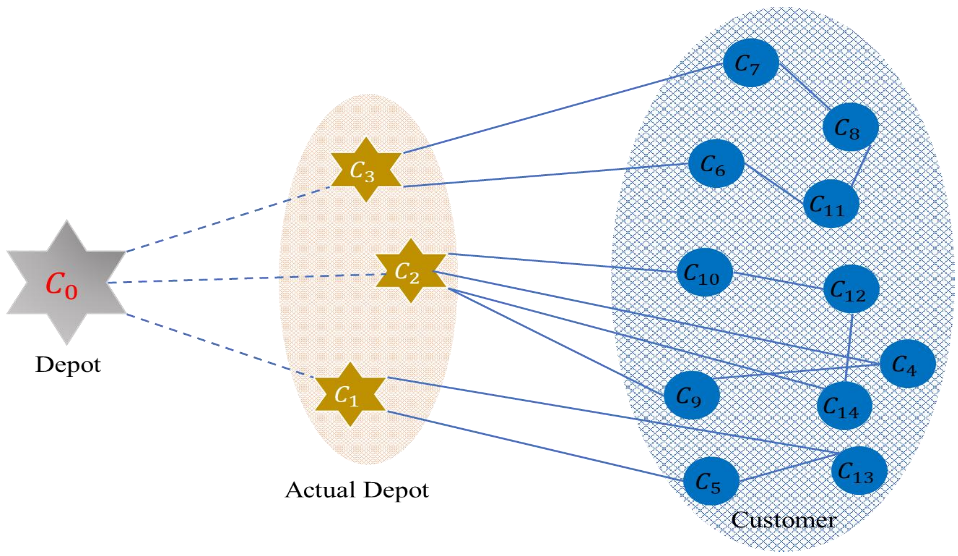

Fig.5. Fresh Supply Chain Game Optimization Diagram

Based on the definitions and solution algorithms proposed in this paper, Figure 6 illustrates the representation of the solution. Subsequently, the description of the edge selection based on Figure 6 can be as follows: select a tour from the parent solution. Figure 6 depicts the randomly chosen b-th node. The th node and the c-th node are the preceding and succeeding nodes of the selected node, respectively. Randomly select other tours from the same parent solution. For the first selected node, create a set of available nodes for the second route based on vehicle capacity constraints.

The optimization objectives of my model are to minimize energy cost and carbon emissions, with constraints including supply-demand balance and equipment capacity limits. These are largely similar to existing energy optimization models.My model adopts a linear programming algorithm, which is a common method in energy optimization and has advantages of high computational efficiency and reliable results. However, it may not fully capture complex nonlinear factors.The input parameters of my model include electricity demand, generation costs, emission factors, etc., and the output is the optimal operation plan for different power generation technologies. These input/output indicators are comparable to existing models. In terms of accuracy, further validation is needed to assess how well the model results match real-world situations.

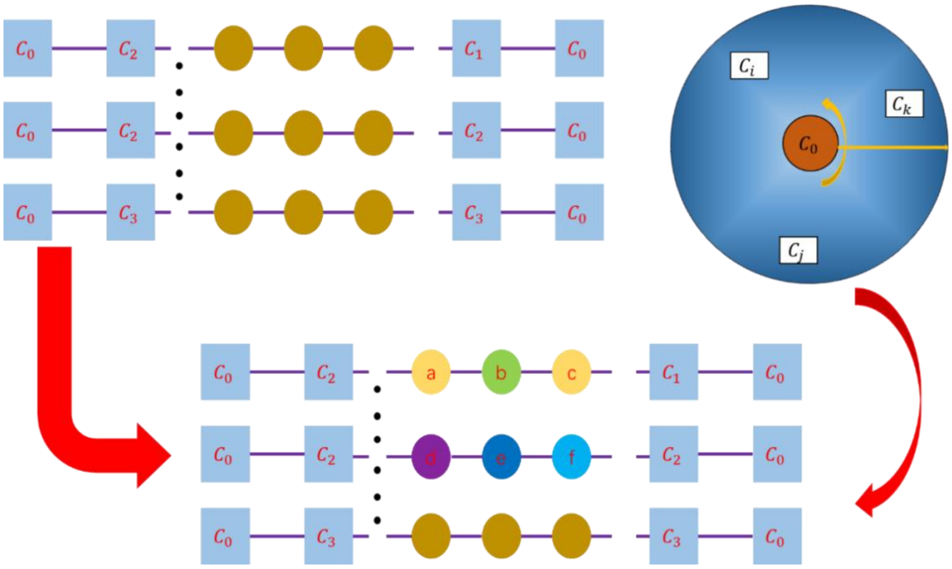

Fig.6. Parent-Child Relationship Diagram

The selection of the second node is influenced by information density, the visibility of edges between the previous/next nodes and the two nodes, and the proximity of the nodes. Assuming the d-th, e-th, and n-th nodes represent three consecutive nodes, the choice of the second selected node in the crossover operation as the th node is determined by the probability rule in Equation (24).

$$p_{be} = \frac{\tau_{ae}^{\alpha} \times \eta_{ae}^{\beta} + \tau_{ec}^{\alpha} \times \eta_{ec}^{\beta} + \tau_{db}^{\alpha} \times \eta_{db}^{\beta} + \tau_{bf}^{\alpha} \times \eta_{bf}^{\beta}}{\sum\left(\tau_{ae}^{\alpha} \times \eta_{ae}^{\beta} + \tau_{ec}^{\alpha} \times \eta_{ec}^{\beta} + \tau_{db}^{\alpha} \times \eta_{db}^{\beta} + \tau_{bf}^{\alpha} \times \eta_{bf}^{\beta}\right)}, \quad e \in \Phi \tag{24}$$

B. Optimization Results Analysis

Based on the above assumptions, we assume the following scenario: a fresh supply chain cold chain logistics transport has a fresh material origin and five logistics warehousing centers, and there are 26 consumers to order fresh products, which is problem A. We preliminarily optimized the origin of raw materials for fresh products as well as the geographical location of five storage centers and consumers. The origin coordinate of raw materials for fresh products is set as [35,35], and the transportation cost of a cold chain logistics truck is 4.5 yuan/km/kg. The loss of goods is 0.12, the price of transport goods is also optimized, according to the proportion of the type of delivery to determine the unit price of goods is 20 yuan/kg, the punitive cost mentioned above is 6.5 yuan/hour/kg, the cold chain logistics vehicle refrigeration and preservation cost is 65 yuan/hour, the cold chain logistics vehicle traveling speed is 40 km/hour, The time window is [70,100] minutes, and it takes another 25 minutes for the cold chain logistics vehicle to unload the goods to the consumer after docking with the consumer. The coordinates between logistics and warehousing centers and consumers, fixed cold storage and fresh-keeping costs and consumer demand are shown in Tables 1 and 2.

Table 1. Coordinate Logistics and Storage Centers and Fix Cold Storage Costs

Logistics and Storage Centers	Coordinates	Fix Cold Storage Costs
A	[31,21]	410
B	[53,18]	325
C	[32,41]	310
D	[37,43]	470
E	[71,56]	385

Table 2. Coordinates of Consumers and Demand

Consumer	Demand	Coordinates (km)	Consumer	Demand	Coordinates (km)

1	21.12	[51,47]	14	32.15	[45,19]
2	32.35	[62,25]	15	21.11	[12,20]
3	23.95	[18,30]	16	25.00	[73,42]
4	21.46	[52,66]	17	23.11	[52,66]
5	21.24	[45,19]	18	24.36	[26,57]
6	33.21	[13,60]	19	32.45	[35,47]
7	25.85	[23,32]	20	35.11	[53,32]
8	22.11	[59,11]	21	24.11	[33,56]
9	31.60	[60,23]	22	23.11	[30,70]
10	15.66	[33,56]	23	32.35	[21,31]
11	25.00	[30,70]	24	22.16	[58,13]
12	31.75	[60,66]	25	22.16	[35,21]
13	25.00	[13,69]	26	26.00	[33,43]

Based on the above discussion, the author set the relevant parameters of the algorithm and made its maximum number of iterations 400 times. After programming the algorithm in MATLAB, the algorithm converged after 30 times of execution. The calculation results show that the average total cost is 3785 yuan, the average full time is 479.83 minutes, and the average CO2 emission is 42.34 kg. An optimal transportation scheme was obtained through the algorithm optimization of the game model; that is, six vehicles were used to complete the distribution task of fresh agricultural products, costing 3689.14 yuan. The real time was 466.26 minutes, and the total CO2 emission was 40.37 kg. In contrast, the traditional mode of transport using eight transport vehicles has a total cost of 3880.86 yuan, a full time of 493.40 minutes, and a total CO2 emission of 44.31 kg.The transportation path's length is shortened by 5.50%, the carbon emission is decreased by 8.9%, and the model's overall cost is reduced by 4.94%.

We changed various fuel oil prices and CO2 emission pricing, as indicated in Figure 7, to examine the link between fuel prices, CO2 emission prices, carbon emissions, and changes in overall costs in optimizing the cold chain distribution path for fresh agricultural goods.

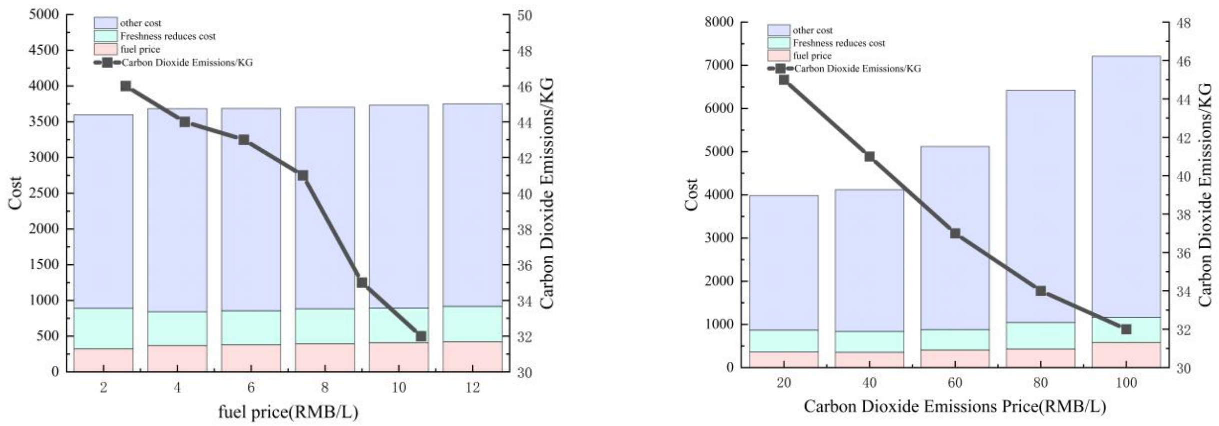

Fig.7 Depicts the Relationships Between Fuel Prices, CO_2 Emission Prices, Carbon Emissions, and Changes in Total Costs

It is clear from Figure 7 that both total expenses and gasoline costs will increase in tandem with rising fuel prices. Concurrently, costs associated with freshness and carbon emissions will be reduced. Furthermore, as carbon prices rise, freshness usually decreases, and carbon emissions generally decrease (Figure 7). Therefore, appropriate fuel or carbon price increases are needed to promote the adoption of low-carbon cold-chain logistics distribution. This measure reduces CO2 emissions and energy consumption and lowers overall enterprise costs. These experimental results can serve as a reference for the government in formulating corresponding policies and regulations.

In the sensitivity analysis experiment, the variance volatility was changed by changing the standard deviation of demand while keeping other parameters unchanged. The variance volatility was increased by 0.1 times, that is, the standard deviation of end customers was increased by 0.1 times of the initial standard deviation each time. The increase of each index of refrigeration cost in the transportation process is shown in Figure 8 as the experimental results of volatility sensitivity analysis.

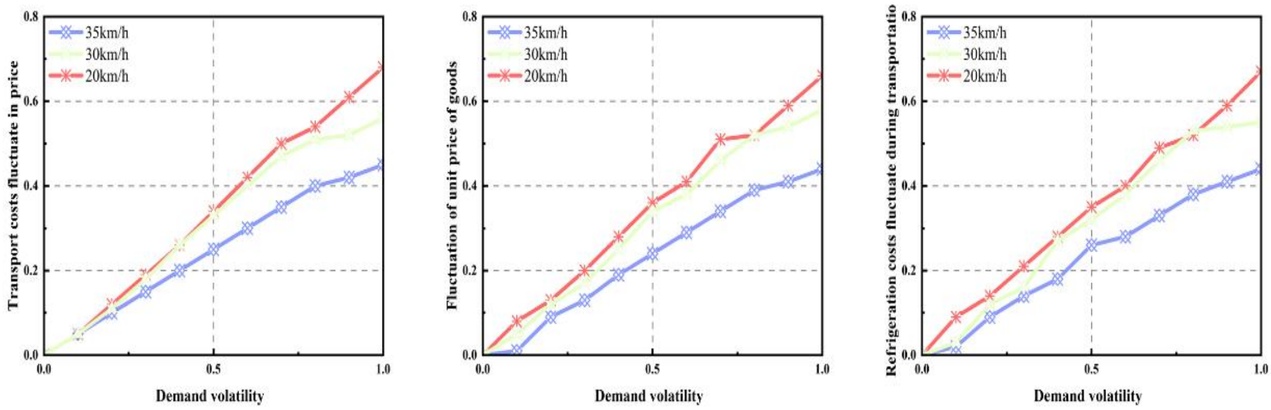

Fig.8. Sensitivity Analysis of Demand to Price Fluctuations

The above situation indicates that demand volatility has an impact on all costs. In summary, from the fluctuation of demand volatility on supply chain optimization target value under different transport speeds, it can be seen that controlling transport speed at 25km/h can effectively mitigate the impact of demand volatility on supply chain operation efficiency.

The model can provide support for the development and enforcement of environmental regulations. By analyzing supply chain data and identifying nodes with high environmental impact, your model can provide targeted recommendations and measures to help monitor and improve the sustainability performance of your supply chain. For example, high carbon emissions can be identified, motivating relevant stakeholders to take mitigation measures and promoting enforcing environmental regulations. At the same time, applying supply chain energy management will also impact policymaking. By optimizing energy consumption and improving energy efficiency, it can help reduce energy consumption and carbon emissions in the supply chain. This will be relevant for policymakers

This model may have a positive ecological impact on the supply chain by optimizing energy use and reducing resource waste. This study will help reduce carbon emissions and environmental pollution and improve the ecosystem's health. This will positively affect ecological balance and biodiversity conservation and contribute to sustainable development. The model may bring economic benefits to the supply chain. By optimizing energy management and reducing resource waste, this study can reduce operational costs, increase efficiency, and improve the sustainability performance of the supply chain. This will bring financial rewards to businesses and encourage more organizations to adopt sustainable supply chain management methods.

4. Conclusion

This paper initiates from the perspective of differential games and establishes a resource-efficient smart energy system based on the fundamental principles of game theory. The crux of addressing the issues of resources and conservation in the smart energy system lies in the intelligent management of energy and the utilization of renewable energy, achieved through Reinforcement Learning (RL) algorithms and game theory. Simultaneously, the paper conducts an optimized design study on the cold chain transportation issue within the fresh supply chain through the energy management system. It emphasizes that the vehicle routing problem is a crucial aspect of cold chain logistics distribution, serving as a key link to reducing overall distribution costs and carbon emissions. Using MATLAB programming to solve the model proposed based on differential games, the paper derives the following results and conclusions:

1. Compared with traditional models, the proposed model reduces the scheduling of two refrigerated trucks, the transportation path's length is shortened by 5.50%, the carbon emission is decreased by 8.9%, and the model's overall cost is reduced by 4.94%.

2. This study suggested an optimization model for cold chain transportation in the fresh supply chain, which may efficiently optimize the fresh product transportation chain and lower expenses and carbon emissions. The model is based on the fundamental ideas of game theory. This paradigm has some guiding relevance and practical application value.

3. Based on the differential game between energy and cost, this paper presents the basic model of a smart energy system and an intelligent power grid. However, another challenge lies in the limited data for optimizing energy usage. This problem may be solved by installing smart meters and other sensors to gather information on energy use and then using data analysis to examine and optimize energy use.

This paper has yet to consider the possible contract coordination and incentive mechanism behavior strategies of production and processing enterprises in the supply chain of fresh agricultural products. Therefore, motivating all nodal enterprises in the supply chain of fresh farm products to jointly choose and actively invest logistics resources through reasonable contract design will be an essential direction for further research in the future. At the same time, the model proposed in this paper can also be optimized and applied to ordinary logistics transportation.

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