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Research Article

Decision Making for Principal-Agent Contracts in Intelligent Customization for New Energy Equipment

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Intelligent manufacturing is a sustainable impetus to development of customization for new energy equipment. Reasonable principal-agent contract decision making can play a positive role in improving utility for customers and securing their long-term involvement. This paper establishes a multistage principal-agent model of intelligent customization for new energy equipment. The principal-agent and intelligent customization decisions, yielding risk avoidance and a better cost-benefit ratio, emerged from solving the model. A decision modification mechanism, used to improve intelligent customization output and consolidate customer trust, was proposed for agents. Research shows that overavoidance of customization risk by new energy equipment manufacturers reduces the efficiency of intelligent customization and aggravates the cost-benefit dilemma. Viewing intelligent customization as a long-term cooperative process, manufacturers can achieve a larger increase in equipment customization output at a smaller cost and enhance customer trust by adopting such a decision modification mechanism. The effect of this mechanism is obvious when the risk intensity is low. However, under the assumption of a multistage model, improvement of customer utility is mainly influenced by risk controllability. This paper provides solutions to the risk avoidance and cost-benefit dilemma problems of intelligent customization. The static principal-agent model was improved to a multistage model by setting the timeline. Long-term effectiveness of the decision modification mechanism was verified using this multistage model.

1. Introduction

New energy equipment (NEE), as the basic tool for the development and utilization of new energy sources, has great significance and research value for the sustainable development of world energy resources. Following the pace of the fourth industrial revolution, NEE manufacturing is transforming to intelligent manufacturing under the influence of industry 4.0 [1]. Without a doubt, intelligent manufacturing for NEE simultaneously meets the dual requirements of energy development and industrial development.

New energy sources include solar energy, wind energy, biomass energy, geothermal energy, nuclear energy, and other unconventional energy sources. NEE refers to a comprehensive suite of equipment, components, and supporting facilities applied to the production of new energy [2]. At present, based on service-oriented logic, manufacturing enterprises begin to transform to service-oriented manufacturing, committing to providing accurate customized services for customers' particular needs in order to secure a competitive advantage [3–5]. Because the application scenario is complex and customer demands are changeable, NEE mainly completes production tasks through order manufacturing, nonstandardized manufacturing, project manufacturing, and so on. Customization refers to goods and services created by enterprises based on the exchange of information regarding customers' individual requirements [6]. The manufacturing of NEE has a high degree of nonrepeatability and customization in equipment research and development, design, production organization, operation, and maintenance services. Intelligent manufacturing systems (IMSs) have the advantages of improving product accuracy, shortening the production cycle, and reducing production costs [7]. As IMS for NEE becomes increasingly mature, a large number of information

interaction platforms, such as product collaborative development services, and lean product development support services, have come into use one after another [8]. The role of customers in transactions is gradually shifting to that of codevelopers, and their particular specifications for special NEE operation requirements in a complex market can be customized through intelligent manufacturing [9].

However, the main source of revenue for intelligent customization of NEE is differentiated demand driven by postcarbon uncertainties. But these uncertainties become risk factors impacting the performance of intelligent customization of NEE when the goal of customer customization is not achieved due to the influence of uncontrollable factors, such as special operating environments for NEE and the limitations of IMS [10, 11]. The impact on performance can easily trigger cost-benefit dilemmas for enterprises. Customization revenue may be lower than expected under the influence of risk factors, but customization can also lead higher costs associated with the complex coordination processes required to define the specific needs of individual customers [12]. The risk factors of customization and intelligent manufacturing that influence the output of intelligent customization for NEE are considered in the model presented here, in order to study how to eliminate the cost-benefit dilemma and risk aversion through optimal manufacturer decisions.

To study the impact of risk factors on output, Jensen et al. introduced risk variables into principal-agent theory, finding that the optimal risk contract can satisfy both optimal performance and risk avoidance objectives [13]. The risk aversion for principal-agent parties will have a significant impact on the contract, and thus will affect the interests of both parties in seeking a cooperative solution [14]. In summary, the impact of risk factors on customization performance should be fully emphasized in the principal-agent relationship between manufacturers and users of NEE. Furthermore, providing a reasonable contract for intelligent customization in order to accomplish risk avoidance and cost-benefit targets is an important management decision-making problem in intelligent customization of NEE.

This paper endeavors to provide an optimal decision model for intelligent customization contracts in the NEE manufacturing principal-agent problem. First, the classical principal-agent model was constructed by analyzing the principal-agent relationship between manufacturers and users. Based on solving the model, we obtained a balanced decision accounting for risk aversion and the cost-benefit dilemma. We also analyzed the characteristics of the solution and put forward some corollaries that factors influencing optimal decision making. Second, the classical principal-agent model as a multistage model of long-term performance was improved by using the time axis to simulate the long-term development process of intelligent customization for NEE. Meanwhile, we proposed a modification mechanism for decision making. Last, the conclusion of the research and the effectiveness of the modification mechanism were validated and illuminated by numerical analysis. Hence, this study not only provides a decision-making method for overcoming the cost-benefit dilemma and satisfying risk aversion, but also proposes a sustainable management strategy for intelligent customization of NEE in the process of long-term development.

This paper's key innovation lies in considering the influence of risk factors on the principal-agent relationship. The classical principal-agent model was improved as a multistage model of long-term performance by configuring the time axis to provide evidence for decision making that avoids risks, resolves the cost-benefit dilemma, consolidates manufacturer-customer cooperation, and enhances long-term development capacity for NEE customization.

2. Literature Review

Intelligent manufacturing originated in Japan. In 1990, the International Cooperation Research Plan for Intelligent Manufacturing System (IMS) was formulated to promote the transformative upgrading of Japanese manufacturing industries [15]. In recent years, key technologies such as artificial intelligence, cloud computing, and cyber-physical systems, which are the basis of the IMS, have developed rapidly and have demonstrated their application value. The IMS has made real practical breakthroughs. Academic researchers also continue to update the theoretical model of intelligent manufacturing, whose benefits have been amply demonstrated. On the one hand, at the level of enterprise management scholars, the perfect enterprise IMS is based on professional technology. In these studies, multiagent technology is widely used in research on distributed IMS and is considered an effective method for process optimization [16]. The application of this technology is very effective for shop-scheduling optimization, shortening the product customization cycle, and enhancing product manufacturing agility [17–19]. On the other hand, with the rise of service-oriented manufacturing theory, IMS principles can be applied to the production organization task of individualized product orders [19, 20]. Further, researchers have proposed that an IMS should implement differentiated production of product attributes with the aim of solving the special needs of customers [9, 21, 22]. The integration of manufacturing technology and production equipment is very critical for enhancing customization capability [23]. The reconfigurability of intelligent manufacturing system helps to meet the individual needs [24]. In further research studies, the boundaries of the IMS break through the boundaries of production units such as enterprises and workshops. Ying et al. fully emphasizes the importance of an intelligent manufacturing ecosystem based on social cooperation for the sustainable development of intelligent manufacturing [25]. This further illustrates the importance of customer participation in realizing customization functionality in intelligent manufacturing.

The new energy industry is rapidly developing in many countries. But there are still several problems in large-scale industrialization. Manufacturing of NEE is one of those problems, especially its development trajectory [26]. There are two widely recognized views of research on how NEE manufacturing will develop. One is a transformative shift to intelligent manufacturing. In the NEE manufacturing process, the application of intelligent equipment can significantly

reduce production costs and improve product accuracy [27]. In view of this development direction, Meng and Yu and Meng and Li made a comprehensive survey of the factors influencing the intelligent transformation of NEE manufacturing and proposed a technical roadmap for this transformation [28, 29]. The second view focuses on transformation toward service-oriented manufacturing. Since R&D and design, after-sales service, and other service links are at the high end of the value chain curve, manufacturers clearly attach great importance to the integration of NEE manufacturing with the modern service industry so as to transform their role from equipment manufacturers to comprehensive solution suppliers [30]. With the intensification of specialized division of labor, the reorientation of NEE toward service-oriented manufacturing requires the cooperation of multiple stakeholders applying their respective professional capabilities to complete the structure of the service platform [8].

Generally, NEE is manufactured at large and complex integrated supporting facilities with large ranges for equipment parameters and strong specificity. Accordingly, NEE is highly customized. Advanced manufacturing technology enables mass customization to become a reality [31]. Mass customization of NEE based on the IMS has become an effective way to provide new energy solutions. Within the context of the manufacturing revolution, customization is not only an important strategic goal for manufacturing enterprises building core competitiveness, but also a hot issue in global academic discussions [32–36].

However, there are still a couple of obstacles created by existing manufacturing technology in the real trading environment for enterprises developing intelligent customization. First, in the field of customization management, Gebauer et al. pointed out that for suppliers to master the entire service provision of product production in offering product customization solutions is not too feasible economically. Customization efficiency can, however, be improved by utilizing the supply chain formed by manufacturing service networks [37]. Manufacturers need to pay attention to service innovation when they develop product-centric service projects if they are to maintain competitiveness. Their major challenge is the capability, necessary for service innovation, to perceive and capture needs and allocate resources [38]. Villena et al. pointed out that careless coordination between suppliers and customers can lead to conflicts between them, especially on the issue of cost [39]. This is due to high investment by specialized suppliers in specialized customization business [40].

Second, in the application field of the IMS, obstacles such as lacking the ability to construct an entire IMS or a uniform intelligent technology route suppress the implementation of intelligent customization [28, 41]. Many studies have been carried out on overcoming barriers to customization and improving its efficiency. This research can be categorized into two groups. Some research focuses on strengthening customization capability from the perspective of capacity for enterprise, such as managing customer relationships, processes, and the product life cycle [37–39], while others consider ways to relieve the cost-benefit predicament of enterprises and improve the customization investment efficiency based on analyzing customized transaction costs [42–47]. Improved customization efficiency has an impact on customer satisfaction and has contributed to promoting stable cooperative relationships between customer groups and enterprises and improving enterprise performance [34, 48].

Uncertainties such as these are the main driver of NEE customization as well as the origin of added value. Therefore, the impact of risk factors on customization results should be fully taken into account. A multitask principal-agent model was advanced by Holmstrom and Milgrom based on classical principal-agent theory [49]. Jensen and Murphy pointed out that adding risk variables to principal-agent contracts can increase agents' risk awareness and simultaneously prompt them to improve their efforts [13]. In addition, reasonable contract decision making can provide customers with higher cost-effective goods, thereby eliminating transaction conflicts [50]. Relevant studies on principal-agent theory provide research ideas for risk aversion and optimal contract decision making.

To summarize, the customization of complex products based on the IMS is an active area of manufacturing industry transformation and upgrading research. Academic researchers also recognize the importance of resolving cost barriers, maintaining customer relationships, and using intelligent manufacturing technology to achieve mass customization. Existing research has focused on how to improve customization efficiency using management and thus effectively realize customers' personalized needs. However, few papers focus on the impact on the interests and cooperation of manufacturers and customers when the goal of customization is not fully realized. This means that the risk-aversion problem and the sustainability of customization have not been given enough attention.

To overcome the intelligent NEE customization cost dilemma and maximize the interests of both sides and enable the ongoing development of intelligent customization, this paper builds a principal-agent model for intelligent customization of NEE based on principal-agent theory by considering the manufacturer's risk avoidance target. First, the decision for the balance between risk avoidance and cost-benefit was found by solving for the optimal intelligent customization contract (ICC). Second, a decision modification mechanism, used to improve intelligent customization output and consolidate customer trust, was proposed for agents in order to enhance the capacity for sustainable development of the intelligent NEE customization sector.

3. Theoretical Basis and Model

3.1. Analysis of the Principal-Agent Relationship. In this paper, the aspect of NEE manufacturing studied is the task of manufacturing large-scale special equipment and its necessary components to support new energy development and application projects, for instance photovoltaic generators and their necessary facilities or equipment and necessary facilities for grid-connected or off-grid wind power projects. In such transactions, stakeholders mainly include NEE

suppliers, energy suppliers, and new energy project developers. Equipment suppliers provide special equipment manufacturing services for energy suppliers' new energy development projects. That is, energy suppliers or new energy project developers are the customers of equipment manufacturers. Manufacturers of such products, who aim to adapt to specific operating environments and customers' personalized needs, provide customers with complete NEE solutions. From the perspective of industrial engineering, manufacturers first need to understand the climatic and geographical conditions of equipment operating sites before they can design targeted equipment function parameters and customize new energy projects comprehensively based on customers' load requirements. Second, manufacturers perform customized tasks for corresponding equipment based on the IMS. This resolves the contradictions between large-scale production in traditional manufacturing enterprises and individualized customization and creates mass customization without excessive human intervention.

From a science and technology management perspective, customers entrust their energy needs to manufacturers in the trade and conversely manufacturers achieve customer goals as agents based on intelligent manufacturing. This implies a principal-agent relationship in their dealings, and based on this relationship, manufacturers will interact fully with customers, provide completely new personalized energy solutions, and tailor production to the actual situation. Whether a manufacturer can achieve a customer's demands through cooperative development depends on two tasks. One is the customization of products. Only when the manufacturer fully understands the customer's personalized needs and effectively investigates the equipment operating environment can an accurate customization plan to improve equipment specificity be made. However, in the process of cooperative development, customer needs reveal both explicit knowledge that can be clearly stated and tacit knowledge that is difficult to express, a situation which could cause deviation between the equipment manufacturing target and the customer's requirement [51]. Therefore, manufacturers need to invest more high-quality technical resources to understanding customers' requirements and coordinating between these requirements and production, using data analysis, on-the-spot investigation, and technical support to ensure the goals of the two sides are as consistent as possible.

The other task is the execution of NEE's customization plan through intelligent manufacturing. The IMS resolves the contradiction between mass production and personalized customization by executing the production tasks of personalized orders quickly. The IMS based on artificial intelligence technology coordinates the subsystems of discrete manufacturing of complex products with minimal human intervention by monitoring and commanding on cloud and greatly improves customization efficiency and precision.

To sum up, we establish a principal-agent relationship between manufacturers and customers of NEE based on intelligent customization service. The manufacturer or agent provides precise new energy solutions for clients through customized design and intelligent manufacturing.

3.2. Hypotheses of the Model

Hypothesis 1 (information asymmetry). There is an information asymmetry between customers and manufacturers in the principal-agent relationship for intelligent NEE customization [52]. Clients do not understand the principles of industrial engineering in the manufacturing of NEE, as well as the operation process of the IMS. Clients cannot observe the agent's investment level in intelligent customization, but can only evaluate customization results through NEE performance. Therefore, agents have more information about the transaction.

Hypothesis 2 (risk). Risk is the key content studied in this paper. Model output is the NEE customization result. The essence of output is the customer's perception of the product value based on uniqueness, function, and other indicators [53]. The major uncertainties affecting NEE customization results emerge mainly from the process of customization design and intelligent manufacturing, and the main factors affecting the design of customization include climate, landform, and customer's energy load. When unpredictable circumstances arise, the NEE will perform poorly in specific operating environments because those factors are very difficult to control. In addition, the purpose of customization is held back by insufficient integration of NEE manufacturing and the IMS.

Therefore, in this paper, two main tasks of intelligent customization of NEE are modeled as two input-output functions, $\mathrm{X}_1(n_1)$ and $\mathrm{X}_2(n_2)$. The former concerns customized design while the latter models intelligent manufacturing. Considering the solvability of the model and learning from the research method in Liu's research [54], the task output function is set to a linear function:

$$\mathrm{X}_i = k_i n_i + \theta_i, \quad i = 1, 2. \tag{1}$$

In this function, n_i represents the necessary technology input that the manufacturer should complete two main tasks. The output coefficient for the technology input is represented by k_i, while the uncertainty effect of intelligent customization risk on output is represented by θ_i. The uncertainties are an important motivating reason for NEE customization. Because the composition of these necessary inputs is very complex, we use the total input n_i to model. Evaluation of output should be further decomposed to facilitate numerical analysis in obtaining effective data. In this paper, the benefit of equipment customization input is divided into three parts: environmental adaptability $k_{11}n_1$, energy output efficiency $k_{12}n_1$, and customer demand satisfaction $k_{13}n_1$. The benefits of intelligent manufacturing investment can be divided into production cycle reduction $k_{21}n_2$, labor input reduction $k_{22}n_2$, and invalid resource consumption reduction $k_{23}n_2$. The output function of the model is further refined:

$$X_i = \sum_{j=1}^{3} k_{ij} n_i + \theta_i, \quad i = 1, 2. \tag{2}$$

For convenience, $\sum_{j=1}^{3} k_{ij}$ is replaced by k_i, which not only increases the specificity of products and thus yields extra profit, but may also adversely affect the operational

Table 1: The notions of mathematical symbols in Section 3.

Symbols	Notions
X_i	The customization output
n_i	The technology input
k_i	The output coefficient
θ_i	The uncertainty of output
σ^i	The variance of distribution of θ_i
v	The principal utility function
u	The agent's utility function
w	Part of the output obtained by the agent
ρ	The risk avoidance degree of agents
b_i	The cost coefficient
r	The correlation between two tasks
α	The fixed cost
β	The distribution coefficient
RC	The risk cost
ΔC	The saving costs
AC	The agent cost

Table 2: The notions of mathematical symbols in Section 4.

Symbols	Notions
y_t	The principal's trust in the agent
π_{it}	The customized output for the current period
$\Delta\pi_{it}$	The output fluctuation caused by uncertainties
β_{1t}^*	The optimal output-sharing coefficient in the current period
$\overline{\beta_{it}}$	The output-sharing coefficient affected by y_t

performance of equipment. So, θ_i should be a random variable with normal distribution $\theta_i \sim N(0, \sigma^i)$ according to Ma and Meng's principal-agent model, whose density function is $f(\theta_i)$ [55]. Due to the various uncertainties affecting the two main tasks of intelligent customization of NEE, θ_1 and θ_2 are independent of each other.

Hypothesis 3 (risk traits). In the process of customizing NEE, manufacturers have clearer perceptions of output risks and are better at avoiding such risks through technical means than customers. Therefore, the principal is assumed to be risk neutral in the model. The agents are risk averse with an inconvenient absolute risk aversion. The principal's observation of output includes two agent task outputs X_1 and X_2 according to the relative utility of risk. The principal utility function is $v = X_1 + X_2$ as risk-neutral characteristics, whose second derivative $v'' = 0$. The utility function of agents is $u = g - e^{-\rho w}$, with $u'' = -\rho^2 e^{-\rho w} < 0$ according to the risk-aversion characteristics [56], meaning that the agent is strictly risk averse. There exists a variable g for which $V(X_1, X_2) \in \mathbb{R}$, $u > 0$ is true. The variable w is part of the output obtained by the manufacturer in the customized contract. Risk avoidance degree of agents used to explain the agent's attitude to risk is represented by ρ.

Hypothesis 4 (negative utility of input). Referring to the principal-agent model of cost-negative utility research, the cost-negative utility of a single-task technology input n_1 is modeled by a simple quadratic function: $C(n_i) = b_i(n_i^2/2)$. The negative utility function of the technology input of the two tasks is as follows:

$$C(n_1, n_2) = \frac{b_1 n_1^2 + b_2 n_2^2 + r n_1 n_2}{2}, \tag{3}$$

where b_1 denotes the cost coefficient. The correlation coefficient between the two customized tasks is r, reflecting the correlation between two tasks. If $-1 \le r < 0$, the cost of agents completing two tasks at the same time is less than the cost of individual execution when two tasks are complementary. If $0 < r \le 1$, the cost is more than the individual costs and the two tasks are alternative. In particular, when $r = 1$, they are completely alternative tasks; the tasks are completely complementary when $r = 1$ and completely independent when $r = 0$.

Hypothesis 5 (intelligent customization contract (ICC)). Designing a reasonable ICC is one of the main aspects of this paper. In the principal-agent relationship for intelligent NEE customization, customized output is distributed between manufacturer and customer. The distribution scheme is captured by the ICCs under study. Theoretical studies show that linear distribution contracts can achieve the best balance between risk aversion and revenue goals under the information asymmetry scenario [57]. Let α be the fixed cost paid by the customer to the manufacturer, and let the distribution of variable output be determined by the distribution coefficient β. Then, the agent's distribution function in a linear ICC is as follows:

$$s(X_1, X_2) = \alpha + \beta_1 X_1 + \beta_2 X_2. \tag{4}$$

3.3. Modeling. In the principal-agent relationship, the ICCs provided by NEE manufacturers as agents should solve two core problems. On the one hand, the ICCs provided by the manufacturer should be able to meet the manufacturer's risk-aversion requirements. On the other hand, a reasonable technology investment decision can relieve the cost-benefit dilemma of customized services. According to Hypotheses 2 and 4, $(\mathrm{d}x_i/\mathrm{d}n_1) > 0$ and $(\partial C/\partial n_1) < 0$. These two inequalities show that there is a logical contradiction between customers' and enterprises' interests. The former inequality shows that customers hope that manufacturers can improve their level of technological input to create NEE with better performance. But the latter inequality implies that higher technology input will make enterprises fall into the cost dilemma. In fact, Pareto optimality of risk sharing is unachievable in the information asymmetry scenario, meaning that the above contradictions cannot be thoroughly resolved [57]. Accordingly, the goal of establishing an intelligent customization principal-agent model for NEE is to balance risk sharing and optimal investment.

First, the modeling process allows the ICCs provided by the manufacturer to maximize the utility of customers, setting the problem (P) to solving for the optimal output-sharing coefficient and the optimal technological input. Second, two constraints from the agent restrict the decision.

In the first, participation construction, the expected utility obtained by an agent in accepting a contract cannot be less than the maximum expected utility obtained when they do not accept a contract. The second constraint is incentive compatibility: given actions by the agent which the client cannot observe, under any incentive contract the agent always chooses the actions that maximize its expected utility. The interests of the principal and agent are measured by certainty-equivalent income [58]. Their interests are calculated by Hypotheses 1–5.

The principal's certainty equivalence income is

$$\begin{aligned}\exp(\mathrm{v}) &= \int\int_{-\infty}^{+\infty} v(X_1, X_2) f(\theta_1, \theta_2)\mathrm{d}\theta_1\mathrm{d}\theta_2 \\ &= -\alpha + \int_{-\infty}^{+\infty}(1-\beta_1)(k_1n_1+\theta_1)f(\theta_1)\mathrm{d}\theta_1 \\ &\quad + \int_{-\infty}^{+\infty}(1-\beta_2)(k_2n_2+\theta_2)f(\theta_2)\mathrm{d}\theta_2 \\ &= -\alpha + (1-\beta_1)k_1n_1\int_{-\infty}^{+\infty}\theta_1 f(\theta_1)\mathrm{d}\theta_1 \\ &\quad + (1-\beta_2)k_2n_2\int_{-\infty}^{+\infty}\theta_2 f(\theta_2)\mathrm{d}\theta_2 \\ &= -\alpha + (1-\beta_1)k_1n_1\lim_{\theta_1\longrightarrow+\infty}F(\theta_1) \\ &\quad + (1-\beta_2)k_2n_2\lim_{\theta_2\longrightarrow+\infty}F(\theta_2) \\ &= -\alpha + (1-\beta_1)k_1n_1 + (1-\beta_2)k_2n_2.\end{aligned} \tag{5}$$

While the agent's certainty equivalence income is

$$\begin{aligned}\exp(u) &= g + \int_{-\infty}^{+\infty} u(w)f(w)\mathrm{d}w \\ &= g + \int_{-\infty}^{+\infty} -e^{-\rho(s(X_1,X_2)-C(X_1,X_2))}f(w)\mathrm{d}w \\ &= g + \int_{-\infty}^{+\infty} -e^{-\rho(s(X_1,X_2)-C(X_1,X_2))} \\ &\quad \cdot \frac{1}{\sqrt{2\pi D(w)}}e^{(w-E(w))^2/2D(w)}\mathrm{d}w,\end{aligned} \tag{6}$$

where

$$\begin{aligned}w &= s(X_1, X_2) - C(X_1, X_2) \\ &= \alpha + \beta_1(k_1n_1+\theta_1) + \beta_2(k_2n_2+\theta_2) - \frac{b_1n_1^2+b_2n_2^2+rn_1n_2}{2}.\end{aligned} \tag{7}$$

It is obvious that w is a random variable consisting of θ_1 and θ_2, which subjects to the normal distribution with expectation $s(X_1, X_2) - C(X_1, X_2)$ and variance $\beta_1^2\sigma_1^2 + \beta_2^2\sigma_2^2$. Thus,

$$\begin{aligned}\exp(u) = {} & \alpha + \beta_1k_1n_1 + \beta_2k_2n_2 - \frac{b_1n_1^2+b_2n_2^2+rn_1n_2}{2} \\ & - \frac{\rho}{2}\left(\beta_1^2\sigma_1^2+\beta_2^2\sigma_2^2\right).\end{aligned} \tag{8}$$

The principal-agent model is based on the principle of maximizing benefits to the customer given participation constraints and incentive compatibility constraints of agents. The model is as follows:

$$\begin{aligned}&\max(-\alpha+(1-\beta_1)k_1n_1+(1-\beta_2)k_2n_2)\ (\mathrm{P}), \\ &s.t.\ \alpha+\beta_1k_1n_1+\beta_2k_2n_2-\frac{b_1n_1^2+b_2n_2^2+rn_1n_2}{2}, \\ &-\frac{\rho}{2}\left(\beta_1^2\sigma_1^2+\beta_2^2\sigma_2^2\right)\geq\overline{w}\ (\mathrm{IR}), \\ &\max\left(\alpha+\beta_1k_1n_1+\beta_2k_2n_2-\frac{b_1n_1^2+b_2n_2^2+rn_1n_2}{2}-\frac{\rho}{2}\left(\beta_1^2\sigma_1^2+\beta_2^2\sigma_2^2\right)\right) \\ &\cdot\ (\mathrm{IC}).\end{aligned} \tag{9}$$

3.4. Solution of Model

3.4.1. Solving. We solve the incentive compatibility constraints by seeking partial derivatives of the IC, finding an optimal solution, $N^*(n_1, n_2)$ by optimizing first-order conditions:

$$\begin{aligned}n_1 &= \frac{\beta_1k_1b_2 - r\beta_2k_2}{b_1b_2 - r^2}, \\ n_2 &= \frac{\beta_2k_2b_1 - r\beta_1k_1}{b_1b_2 - r^2}.\end{aligned} \tag{10}$$

The agent's technical input is affected by the change of output distribution coefficient β_i under the condition that the relevant parameters are given. Put, $N^*(n_1, n_2)$ into problem P and IR to solve for the optimal distribution coefficient by constructing the Lagrange function. The solution is as follows:

$$\beta_1 = \frac{k_1^2k_2^2 + \left(k_1^2b_2 - rk_1k_2\right)\rho\sigma_2^2}{k_1^2k_2^2 + \rho k_1^2b_2\sigma_2^2 + \rho k_2^2b_1\sigma_1^2 + \rho^2\sigma_1^2\sigma_2^2(b_1b_2 - r^2)}, \tag{11}$$

$$\beta_2 = \frac{k_1^2k_2^2 + \left(k_2^2b_1 - rk_1k_2\right)\rho\sigma_1^2}{k_1^2k_2^2 + \rho k_2^2b_1\sigma_1^2 + \rho k_1^2b_2\sigma_2^2 + \rho^2\sigma_1^2\sigma_2^2(b_1b_2 - r^2)}. \tag{12}$$

3.4.2. Discussion of the Solution. The optimal ICC that balances the cost-benefit dilemma and risk aversion for the manufacturer is determined according to β_1 and β_2. The output-sharing coefficient in the contract is related to the manufacturer's risk avoidance, the relevance coefficient among intelligent customization tasks, and uncertain random variable parameters affecting output. Based on the form of the solution, the possible solutions' characteristics in terms of the principal-agent model are analyzed as follows.

Corollary 1. *The ICC provided by NEE manufacturers is influenced by their risk-aversion characteristics. The allocation coefficient of the contract is negatively correlated with*

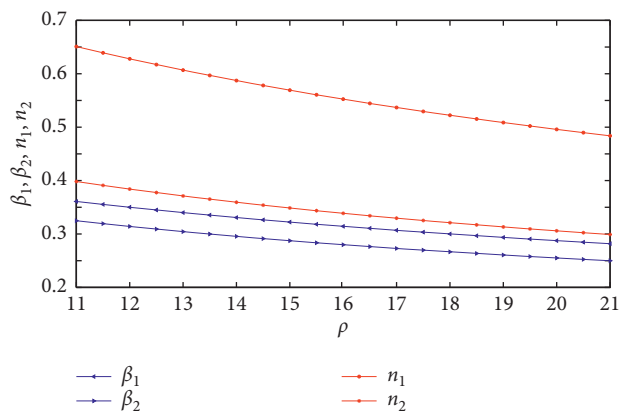

Figure 1: The effect of ρ on β_i and n_i.

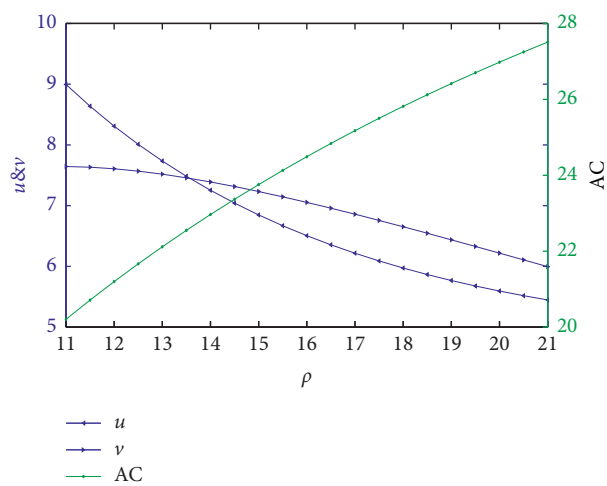

Figure 2: The effect of ρ on u, v, and AC.

the agent's risk aversion. An enterprise will reduce its claim for the output of customization if it has a high degree of risk aversion.

Manufacturers should encourage customers to accept high-return ICCs and accept the associated risks by reducing intelligent customization fees to achieve optimal risk sharing.

Proof. To simplify the proof process without losing generality, we assume that $k_1 = k_2$, $b_1 = b_2$, and $\sigma_1^2 = \sigma_2^2$. Then,

$$\beta_1^{(1)} = \frac{k^4 + (k^2 b - rk^2)\rho\sigma^2}{k^4 + 2\rho k^2 b\sigma^2 + \rho^2\sigma^4 (b^2 - r^2)}. \tag{13}$$

The denominator and the numerator are considered as two parameters A and B, respectively, where $B = k^4 + 2\rho k^2 b\sigma^2 + \rho^2\sigma^4 (b^2 - r^2)$ and $A = k^4 + (k^2 b - rk^2)\rho\sigma^2$. It can be seen that $\beta_1^{(1)}$ is greater than zero according to the value of the sharing coefficient. The derivative of A and B with respect to ρ is as follows:

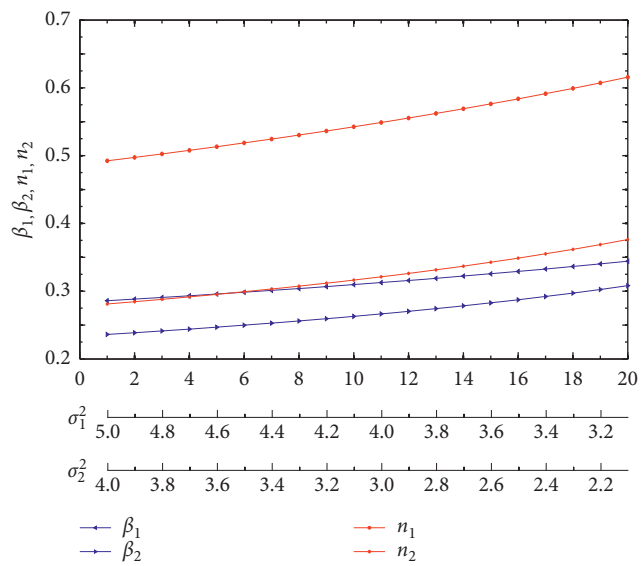

Figure 3: The effect of σ_i^2 on β_i and n_i.

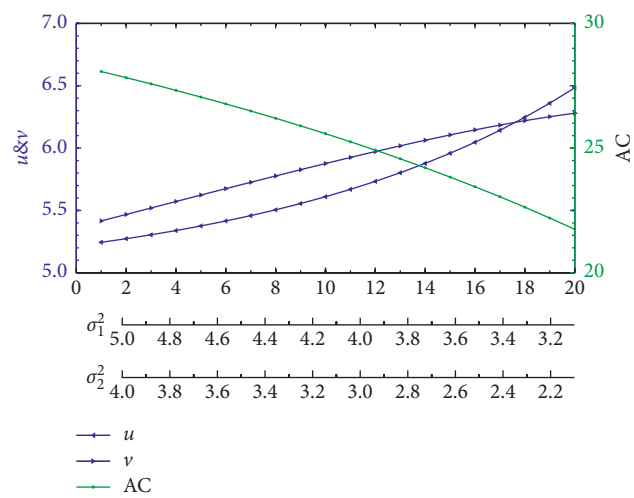

Figure 4: The effect of σ_i^2 on u, v, and AC.

$$\begin{cases} \dfrac{dA}{d\rho} = 2k^2 b\sigma^2 + 2\sigma^4 (b^2 - r^2)\rho > 0, \\ \dfrac{dB}{d\rho} = k^2 (b - r)\sigma^2 > 0, \end{cases} \tag{14}$$

where according to the characteristics of the technical input solution, $n_1 > 0$ and $(b^2 - r^2) > 0$, so $(b - r) > 0$ and formula (15) is valid:

$$\frac{dA}{d\rho} - \frac{dB}{d\rho} = 2\sigma^4 (b^2 - r^2)\rho + k^2 (b + r)\sigma^2 > 0. \tag{15}$$

Because $\beta_1^{(1)} > 0$ and $(dA/d\rho) - (dB/d\rho) > 0$, the increase in the denominator A is greater than that in the numerator B when ρ increases. Therefore, it can be ascertained that $(d\beta_1^{(1)}/d\rho) < 0$. The correctness of Corollary 1 has been established. □

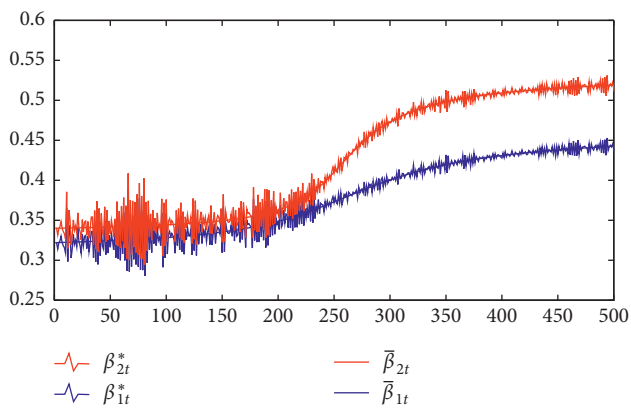

Figure 5: Changes of $\overline{\beta}_{it}$ and β^*_{it}.

Corollary 2. *There is a negative correlation between the optimal sharing coefficient and risk intensity. Manufacturers should set a lower sharing coefficient in the ICC if uncertainty has a strong influence on intelligent NEE customization output. When σ_i^2 is very large, the customization of equipment output fluctuates greatly. Because enterprises have definite risk-aversion characteristics, the emphasis on intelligent customization output should be reduced to achieve optimal risk sharing. That is, manufacturers incentivize customers to accept high-risk contracts with low customization fees.*

Proof. Crucially, we prove that the effect on β_1 and β_2 is as described when σ_2^2 is fixed and σ_1^2 is variable. The derivative of β_i with respect to σ_i^2 is as follows:

$$\frac{\partial\beta_1}{\partial\sigma_1^2}=\frac{-\left[k_1^2k_2^2+\left(k_1^2b_2-rk_1k_2\right)\rho\sigma_2^2\right]\times\left[\rho k_2^2b_1+\rho^2\sigma_2^2\left(b_1b_2-r^2\right)\right]}{\left[k_1^2k_2^2+\rho k_1^2b_2\sigma_2^2+\rho k_2^2b_1\sigma_1^2+\rho^2\sigma_1^2\sigma_2^2\left(b_1b_2-r^2\right)\right]^2},$$

$$\frac{\partial\beta_2}{\partial\sigma_1^2}=\frac{-r\left[k_1^2k_2^2+\left(k_2^2b_1-rk_1k_2\right)\rho\sigma_2^2\right]}{\left[k_1^2k_2^2+\rho k_2^2b_1\sigma_1^2+\rho k_1^2b_2\sigma_2^2+\rho^2\sigma_1^2\sigma_2^2\left(b_1b_2-r^2\right)\right]^2}. \tag{16}$$

It is obvious that β_i and n_i are positive numbers. So, $(k_1^2b_2-rk_1k_2)$ and $(b_1b_2-r^2)$ are greater than zero. Then, $\partial\beta_1/\partial\sigma_1^2$ is less than zero and its sign is determined by r.

From the principal's perspective, customers whose attitude is risk neutral accept the existence of risk to a certain extent. So, manufacturers can stimulate customers to accept customized contracts for NEE using a low customization cost strategy. From the perspective of the agent, because the two customization tasks are related to each other, the change in risk of one task must affect the output-sharing coefficient of another. When two customized tasks are complementary, $-1\le r<0$, we have $(\partial\beta_2/\partial\sigma_1^2)>0$; when they are substituted, $0>r\ge 1$ we have, $(\partial\beta_2/\partial\sigma_1^2)<0$. Finally, when $r=0$ there is no correlation between one task's output-sharing coefficient and the risk intensity of another task. It can be proved that the effect on β_1 and β_2 when σ_1^2 is fixed and σ_2^2 is variable by the same technique. □

Corollary 3. *Based on the incentive compatibility constraints, ICCs provided by the NEE manufacturer can influence decision making about the technology input level. There is a positive correlation between the optimal technology input level and the output-sharing coefficient.*

Proof. Taking n_1 and n_2 as research objects, how does the change of β_1 and β_2 affect decision making for technology input level of the manufacturer? The partial derivatives of objects are as follows:

$$\begin{cases}\dfrac{\partial n_1}{\partial\beta_1}=\dfrac{k_1k_2}{b_1b_2-r^2}>0,\\[2ex] \dfrac{\partial n_1}{\partial\beta_2}=\dfrac{-rk_2}{b_1b_2-r^2},\end{cases}$$
$$\begin{cases}\dfrac{\partial n_2}{\partial\beta_2}=\dfrac{k_2k_1}{b_1b_2-r^2}>0,\\[2ex] \dfrac{\partial n_1}{\partial\beta_2}=\dfrac{-rk_1}{b_1b_2-r^2},\end{cases} \tag{17}$$

where $\partial n_1/\partial\beta_1$ is always greater than zero. The technical input level of a single custom task corresponds consistently with the output-sharing coefficient. But its response direction for the output-sharing coefficient of another task is decided by the relationship between the two tasks. The following are cases discussed for different relationships:

(1) When two tasks are complementary $(-1\le r<0)$, increasing β_1 leads manufacturers to choose a higher technology input level. In this case, there is a positive correlation between n_1 and the output-sharing coefficient β_2 of another task. According to the definition of complementary tasks, the cost of simultaneous execution of two complementary tasks is lower than the sum of the separate execution costs. The manufacturer should further strengthen the level of technology input under the condition that both β_1 and β_2 increase at the same time. Corollaries 1 and 2 show that β_1 and β_2 are affected in the same direction by the change of relevant parameters when two tasks are complementary. Take, for example, an enlargement in which total input is further increased by $\Delta N=(\partial n_2/\partial\beta_1)\mathrm{d}\beta_1+(\partial n_1/\partial\beta_2)\mathrm{d}\beta_2$ on the basis that $N^*=(\partial n_1/\partial\beta_1)\mathrm{d}\beta_1+(\partial n_2/\partial\beta_2)\mathrm{d}\beta_2$. That is to say, the cost savings N^* due to task complementarity are equal to a further increase ΔN.

(2) When two tasks are substitutable $(0<r<1)$, n_1 is positively correlated with β_1 and negatively correlated with the output-sharing factor β_2 of another task. Based on the definition of alternative tasks, the cost of simultaneous execution of two such tasks are greater than the sum of the separate execution costs. Total cost increases by rdn_1dn_2 on the basis of the sum of individual execution because of the existence of substitution. Thus, the technology input level of another task should be reduced to save costs and so achieve the optimal solution of the problem IC. □

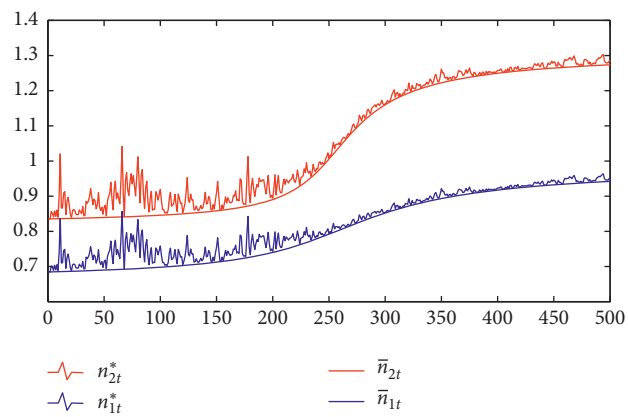

FIGURE 6: Changes of $\overline{n}_{it}$ and n^*_{it}.

3.4.3. Agency Cost. The essence of agency cost is the loss of total welfare as a response to the efficiency of intelligent customization [59]. There are two kinds of agency costs in the intelligent NEE customization principal-agent relationship. One is the risk cost caused by the failure of Pareto optimal risk sharing. The other is the amount of savings by which the expected output reduces the input cost per the optimal technology input level strategy.

First, the risk cost is as follows:

$$\mathrm{RC} = \frac{\rho}{2}\left(\beta_1^2\sigma_1^2 + \beta_2^2\sigma_2^2\right). \tag{18}$$

Second, the amount of savings is calculated as follows. Say the optimal technology input level under a symmetric information scenario is N_0 (n_1, n_2). At this time, the optimal output-sharing coefficient of customization is zero. N_0 is determined by the following:

$$\begin{aligned} &\max\left(-\alpha + k_1 n_1 + k_2 n_2\right), \\ &\text{s.t. } \alpha + \frac{b_1 n_1^2 + b_2 n_2^2 + r n_1 n_2}{2} \geq \overline{w}. \end{aligned} \tag{19}$$

Construct the Lagrange function and solution N_0:

$$N_0 = \begin{pmatrix} \dfrac{k_1 b_2 - r k_2}{b_1 b_2 - r^2} \\ \\ \dfrac{k_2 b_1 - r k_1}{b_1 b_2 - r^2} \end{pmatrix}. \tag{20}$$

The amount of saving costs is ΔC:

$$\begin{aligned} \Delta C &= (k_1, k_2)\left(N_0 - N^*\right)^T - \left[C(N_0) - C(N^*)\right] \\ &= \frac{(1-\beta_1)k_1^2 b_2 - (1-\beta_2) r k_1 k_2 - b_1 A - b_2 B - rC}{b_1 b_2 - r^2}, \end{aligned} \tag{21}$$

where

$$\begin{cases} A = \left[(1+\beta_1)k_1 b_2 - (1+\beta_2) r k_2\right]\left[(1-\beta_1)k_2 b_1 - (1-\beta_2) r k_2\right], \\ B = \left[(1+\beta_2)k_2 b_1 - (1+\beta_1) r k_1\right]\left[(1-\beta_2)k_2 b_1 - (1-\beta_1) r k_1\right], \\ C = \left[(1-\beta_1)k_1 b_2 - (1-\beta_2) r k_2\right]\left[(1-\beta_2)k_2 b_1 - (1-\beta_1) r k_1\right]. \end{cases} \tag{22}$$

Finally, the agent cost AC is RC − ΔC.

All the notions of the symbols used in the mathematical model in Section 3 are shown in Table 1.

4. Multistage Principal-Agent Model

Our multistage principal-agent model is built based on the original hypothesis by introducing the time axis and putting forward new hypotheses which are used to simulate the impact of accumulation on customer trust and technological progress on the principal-agent relationship, in order to analyze the effectiveness of decision making in the long-term development of intelligent NEE customization.

4.1. Multistage Hypothesis of Intelligent Customization

Hypothesis 6 (technological progress hypothesis). Technology customization capability has a positive impact on customization results [9]. In the development of intelligent NEE customization, manufacturers have a more accurate understanding of the relationship between uncertainties and NEE customization due to developing energy technology, upgrading of intelligent manufacturing technology, and accumulation of customization experience. The optimization of equipment parameters and the selection of key components make NEE more specific and adaptable in the special application environment. Meanwhile, as the development of related disciplines become more mature, precise analysis of customization information in the IMS makes equipment more suitable for customization objectives. In a multistage model, the uncertainties can be changed to reflect technological progress in intelligent customization. Suppose that $E\theta_i$ and σ_i^2 are functions of time t, $(dE\,\theta_i/dt) > 0$ and $(d\sigma_i^2/dt) < 0$. During this process, the mathematical expectation of uncertain output θ_i increases gradually while the risk intensity for equipment customization output σ_i^2 decreases gradually. This setting reflects improved controllability of uncertain factors and the decreasing influence of these factors on output.

Hypothesis 7 (accumulation of trust). Customization enables customers and suppliers to establish close cooperation, with a positive impact on manufacturers' customization revenue [60, 61]. The establishment of trust in the relationship is based on customers' comprehensive evaluation of the performance of NEE. In addition, however, fluctuation of output will affect the stability of the trust relationship between the principal and agent. The customer's trust in the manufacturers y_t is established in such a way that

$$y_t = y_{t-1} + \frac{(1-\beta_{1t}^*)\Delta\pi_{1t} + (1-\beta_{2t}^*)\Delta\pi_{2t}}{\pi_{1(t-1)} + \pi_{2(t-1)}}. \tag{23}$$

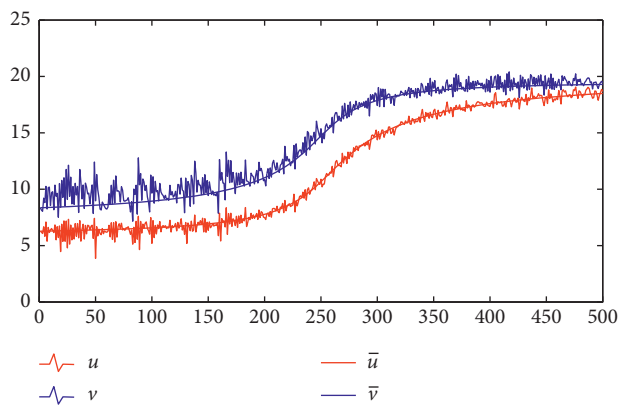

Figure 7: Changes of deterministic equivalent income $\bar{v}$, v, $\bar{u}$, and u.

The impact of trust building on customized contracts is then

$$\overline{\beta_{it}} = \frac{\beta_{it}^{*} y_t}{y_{t-1}}, \tag{24}$$

where β_{1t}^{*} is the optimal output-sharing coefficient in the current period, customized output for the current period is represented by π_{it}, and $\Delta\pi_{it}$ is the output fluctuation caused by uncertainties.

4.2. Analysis of Multistage Model. The customer-acceptable ICC is affected by output fluctuation according to Hypothesis 7. This variable is mainly determined by two parameters: the mathematical expectation which can be used to determine whether $\Delta\pi_{it}$ is positive or negative and the degree of dispersion of uncertain output, which determines its absolute value. Meanwhile, the change of β_{it} also affects the distribution of the original output. The new β_{it} destroys the best balance in the static principal-agent model between optimal risk sharing and the enterprise's interests and invalidates the optimal solution composed of the optimal sharing coefficient of customization contract and the optimal technology input. Therefore, the manufacturer should make corresponding changes in the level of technical input into customization to improve customization performance [62]. If the manufacturer maintains a good cooperative relationship with the customer, the customer's view of the manufacturer will improve based on the enterprise's level of attention [63]. Based on this, we propose a decision-making modification mechanism for technology input in intelligent NEE customization.

When $y_t > y_{t-1}$,

$$\begin{aligned} \overline{n}_{1t} &= \frac{\overline{\beta}_{1t} k_1 b_2 - r\overline{\beta}_{2t} k_2}{b_1 b_2 - r^2}, \\ \overline{n}_{2t} &= \frac{\overline{\beta}_{2t} k_2 b_1 - r\overline{\beta}_{1t} k_1}{b_1 b_2 - r^2}. \end{aligned} \tag{25}$$

When $y_t \le y_{t-1}$,

$$\begin{aligned} \overline{n}_{1t} &= \left(\frac{\beta_{1t}^{*} k_1 b_2 - r\beta_{2t}^{*} k_2}{b_1 b_2 - r^2}\right)\frac{y_{t-1}}{y_t}, \\ \overline{n}_{2t} &= \left(\frac{\beta_{2t}^{*} k_2 b_1 - r\beta_{1t}^{*} k_1}{b_1 b_2 - r^2}\right)\frac{y_{t-1}}{y_t}. \end{aligned} \tag{26}$$

When the equal sign holds,

$$(\overline{n}_{1t}, \overline{n}_{2t})^T = \left(\frac{\beta_{1t}^{*} k_1 b_2 - r\beta_{2t}^{*} k_2}{b_1 b_2 - r^2}, \frac{\beta_{2t}^{*} k_2 b_1 - r\beta_{1t}^{*} k_1}{b_1 b_2 - r^2}\right)^T. \tag{27}$$

Corollary 4. *After introducing Hypotheses 6 and 7 into the principal-agent model, the principal's interests can be optimized by using the abovementioned modification mechanism to adjust customized investment.*

Proof. Three situations in which the agent introduces a modification mechanism with an impact on the principal's interests are discussed.

(1) When $y_t > y_{t-1}$, $\overline{\beta}_{it} > \beta_{it}^{*}$ and the adjusted $(\overline{n}_{1t}, \overline{n}_{2t})^T$ is larger than the original optimal solution based on Corollary 3. Because the principal's utility $(\partial v/\partial n_i) > 0$, when the output-sharing coefficient β_{it} is given, $(\overline{n}_{1t}, \overline{n}_{2t}) > v(n_{1t}^{*}, n_{2t}^{*})$. That is to say, the principal's income after modification is greater than before.

(2) When $y_t < y_{t-1}$, $(y_{t-1}/y_t) > 1$ and we have $(\overline{n}_{1t}, \overline{n}_{2t})^T > ((\beta_{1t}^{*} k_1 b_2 - r\beta_{2t}^{*} k_2/b_1 b_2 - r^2), (\beta_{2t}^{*} k_2 b_1 - r\beta_{1t}^{*} k_1/b_1 b_2 - r^2))^T = (n_{1t}^{*}, n_{2t}^{*})^T$. Since $(\partial v/\partial n_i) > 0$, what is clear is that the principal's income has increased after the modification.

(3) When $y_t = y_{t-1}$, $(\overline{n}_{1t}, \overline{n}_{2t})^T = (n_{1t}^{*}, n_{2t}^{*})^T$. There is no need for modification because the customers' revenue is optimal.

All the notions of the symbols used in the mathematical model in Section 4 are shown in Table 2. □

5. Analysis of Numerical Examples

5.1. Research Objective and Data Collection. This paper takes the intelligent manufacturing of off-grid wind power equipment as a numerical example to analyze optimal ICCs in the principal-agent relationship. Intelligent customization of off-grid wind power equipment relates to corresponding wind power projects. Equipment operation performance is affected by terrain, climate, and wind characteristics of the customer's locale. Therefore, manufacturing projects are highly customized. From the perspective of industrial engineering, customization service of off-grid wind power equipment includes three main stages: predesign, equipment manufacturing, and postservice. First, the manufacturer needs to have a comprehensive understanding of the customer's objectives, usually the load requirements for power consumption activities. The local natural environment should also be fully investigated as a basis for a customized

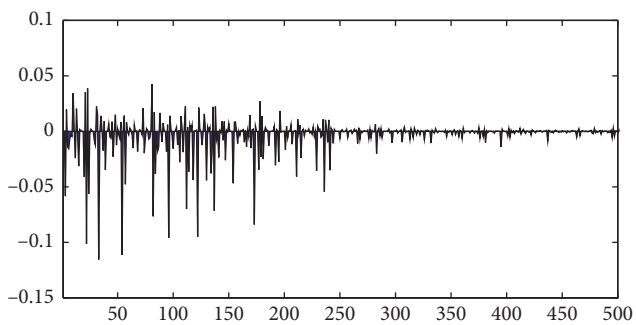

Figure 8: $\bar{v}$ minus v^*.

design of the four main modules of a wind power system, namely, generation, storage, control, and power supply. For example, local wind energy continuity, stability, and customer's energy needs together determine the battery capacity. Temperature characteristics determine the working temperature range of the storage battery and the temperature compensation function for the wind power system controller. Individualized equipment production can then be realized based on the IMS. Off-grid wind power equipment is a representative NEE application with deep integration of customization and intelligent manufacturing. Its individualized manufacturing has the main characteristics of intelligent customization for NEE. Therefore, this paper takes it as a typical example for analyzing the principal-agent model numerically.

With the support of scientific research, the numerical value of the example comes from the investigation of a wind power equipment manufacturing enterprise. The company's main business is machine manufacturing and equipment maintenance in wind power engineering, and it has completed several off-grid wind power projects in China and some Central Asian countries. Moreover, the company is part of the first batch of intelligent manufacturing pilot projects instigated by the Chinese government. With the transformative advent of intelligent manufacturing in recent years, this enterprise has made great progress in shifting to intelligent workshops, management, and service. Numerical values for the example since the enterprise developed an intelligent manufacturing system are determined by enterprise management and intelligent manufacturing engineers in coordination with relevant off-grid wind power project information.

5.2. Analysis of Static Model Examples. We adjust the parameters without affecting the conclusions of the study $\alpha = 9$, $k_1 = \sum_{j=1}^{3} k_{1j} = 21$, $k_2 = \sum_{j=1}^{3} k_{2j} = 17$, $b_1 = 10$, $b_2 = 7$, and $r = -0.1$. The initial values of the parameters for the model are $\rho = 15$, $\sigma_1^2 = 3.7$, and $\sigma_2^2 = 3.5$. Based on Hypotheses 1–3, the parameters are varied to explore their relationship to agency costs. The results of numerical analysis using MATLAB 2014 are shown in Figures 1–4.

Figure 1 shows that in the process of increasing agents' level of risk aversion, the contract allocation coefficient and the optimal technology input gradually decrease. Over-aversion to customization risk leads manufacturers to reduce technology investment in customization and intelligent manufacturing tasks to safeguard their profits. However, this strategy results in a decline in customization performance for wind power equipment and an increase in agency costs, as shown in Figure 2. Although the manufacturer has offered a lower customization fee, the low input obviously reduces the product quality. Therefore, higher risk aversion leads manufacturers to adopt conservative strategies and makes them unwilling to pursue excessive additional customization benefits in the balance of risk and income, resulting in low efficiency of intelligent customization of wind power equipment. This is an important reason for the low efficiency of intelligent customization of wind power equipment.

Figure 3 shows the response of customized contracts and customized inputs to uncertainties. On the premise that the risk aversion of the agent remains unchanged, the ICCs provided by manufacturers are more inclined to obtain output benefits through improving the level of technology input as the strength of the effects expressed by σ_1^2 and σ_2^2 of uncertain factors on equipment operation gradually decreases. Figure 4 shows that the reduction of the influence intensity of uncertainties makes the principal and agent get higher profits in equipment customization. Meanwhile, the agent cost is reduced and the customization efficiency is improved. It is thus clear that although the contract allocation coefficient is higher and the client pays a higher customization cost, manufacturers' high investment did not reduce customer utility. In other words, the customization results of off-grid wind power equipment are better to meet the personalized needs of customers.

5.3. Multistage Model Examples. Multistage models can explore the long-term principal-agent relationship of intelligent customization for wind power equipment based on static models. Based on Hypotheses 1 through 7 and the requirement of operational validity, the new parameters are assigned as $y(0) = 3$ and $t = 500$. According to Hypothesis 6, the parameters $E\theta_i = \mu_i(t)$ and $\sigma_i^2(t)$ of technological progress are as follows:

$$\begin{aligned}
\mu_1(t) &= 3\arctan\left(\frac{t-250}{60}\right) + 4.3542,\\
\mu_2(t) &= 3\arctan\left(\frac{t-250}{30}\right) + 4.3542,\\
\sigma_1^2(t) &= 5 - \arctan\left(\frac{t-250}{60}\right),\\
\sigma_2^2(t) &= 4 - \arctan\left(\frac{t-250}{30}\right),
\end{aligned} \tag{28}$$

where $\mu_i(t)$ and $\sigma_i^2(t)$ are continuous functions of time t. It can be confirmed mathematically that $\mu_i(t)$ is strictly monotonically increasing. Its rate of change is sharply increasing from smooth and is then smooth. The smooth change process simulates the gradual progress of intelligent customization technology. And the period of rapid increase simulates a breakthrough innovation of intelligent customization technology. The corresponding $\sigma_i^2(t)$ is strictly

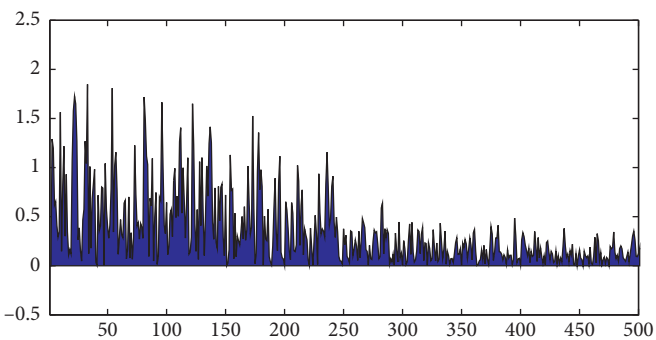

Figure 9: $\overline{u}$ minus u^*.

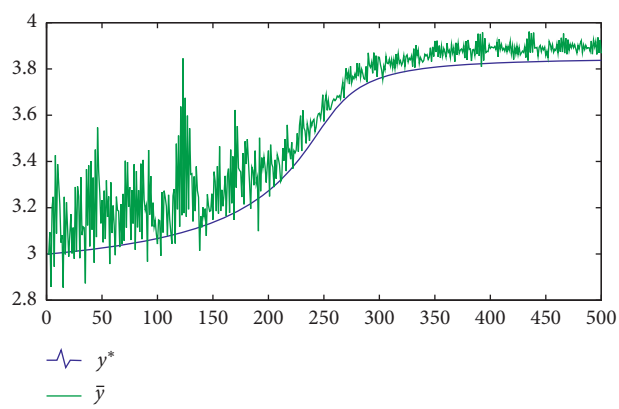

Figure 10: Comparison of $\overline{y}$ and y^*.

monotonically decreasing to simulate increasing controllability of uncertainty factor in the trend of technological progress. In addition, there is a sudden decrease of σ_i^2 corresponding to rising μ_i in the breakthrough innovation phase of intelligent technology. To approach the real trading environment, stochastic processes are used to simulate output risk. The generating parameters of uncertain output are based on $\mu_i(t)$ and $\sigma_i^2(t)$. According to the multistage principal-agent model, the preset parameters are substituted into the model for numerical analysis. The results are shown in Figures 5–10.

Figure 5 shows the change of optimal ICCs during long-term development. Uncertain output makes contract sharing coefficient fluctuate around expected value affect by trust assumption. Under the assumption of technological progress, the modification input level is always greater than the expected value in Figure 6. After the adoption of the modification mechanism, the profits of both parties are shown in Figure 7. The fluctuation of enterprise income around the expected value is relatively gentle, while the fluctuation of customer income around the expected value is mainly positive. This shows that the technology input modification mechanism has benefited customers. Let v^* and u^* be the gains without the modification mechanism. The effects of the modification mechanism are $\overline{v} - v^*$ and $\overline{u} - u^*$, calculations for which are shown in Figures 8 and 9. The value of $\overline{u} - u^*$ is always greater than zero, which shows that the modification mechanism has a beneficial effect on customers' interests. The value of $\overline{v} - v^*$ is less than zero in most cases. When $\overline{v} - v^*$ is greater than zero, manufacturers' income increases $\overline{\beta}_{it} > \beta_{1t}^*$. For cases when $\overline{v} - v^*$ is less than zero, manufacturers sacrifice benefits by adapting the modification mechanisms as $\overline{\beta}_{it} > \beta_{1t}^*$, an effect caused by lower customer revenue. Comparisons between Figures 8 and 9 in matching coordinates show that manufacturers can greatly increase customers' utilities at a lower cost to trust maintenance. This means that the modification mechanism is highly efficient. The change in customer trust calculated by Hypothesis 6 is shown in Figure 10, which shows that the modification mechanism has a significant positive effect on customer trust.

Looking at the overall development trend in intelligent customization for off-grid wind power equipment with the assumption of technological progress, earnings increase gradually for both principal and agent while their volatility decreases gradually. With continuing progress in wind power technology and intelligent manufacturing technology, enterprises continue to deepen their understanding of the impact of natural environments on the off-grid wind power system operation process. Data collection based on field surveys can effectively combine with customer load targets to provide equipment customization information. Equipment customization through IMS can then be realized by manufacturers. The improvement in customers' utility shows that the adaptability of off-grid wind power equipment manufactured by intelligent customization is gradually enhanced in changeable natural environments while customer evaluation of customization results is gradually improving. Under the same assumption of technological progress, manufacturers can make rational decisions on customization input through the principal-agent model, gradually improving benefits on both sides of the principal-agent relationship. The volatility of $\overline{\beta}_{it}$ and $\overline{n}_{it}$ decreased significantly near the presupposed simulation node $t = 250$, representing technological breakthrough innovation. Meanwhile, profitability for both principal and agent is rising rapidly and its volatility is decreasing rapidly toward stability. Under the effect of the modification mechanism, the convergence value of the customization interests of both parties is higher than the expected value. Figures 8 and 9 show a significant change in the strength of the modification mechanism after the technology breakthrough node, with a stronger effect on the improvement of customer utility in the period $t < 250$. After passing the $t = 250$ node, customer utility is enhanced mainly by the controllability of risk factors due to technological progress.

6. Conclusions

This paper studies the role of risk in intelligent NEE customization output. Based on the classical principal-agent model, a multistage model is established by introducing the time axis in order to analyze the optimal contract decision for the manufacturer's goal of risk avoidance while resolving the customization cost-benefit dilemma. An intelligent customization input decision-making modification mechanism is then proposed to

improve the stability of customers' interests and maintain the trust relationship. Finally, a representative numerical case is used to analyze the proposed corollaries and verify the long-term effectiveness of the modification mechanism. The results are as follows.

First, the results of intelligent customization of NEE are influenced by risk factors such as uncertainty in the operational environment and differentiated IMS production capacity. The optimal customization contract (ICC) can not only achieve the purpose of risk aversion but also relieve the cost-benefit dilemma of customization services for manufacturers.

Second, overavoidance of risk reduces the efficiency of intelligent NEE customization of. Excessive risk aversion leads manufacturers to adopt a low-fee strategy to encourage customers to accept risk-based contracts. Since a rational agent, who is limited by the cost-benefit dilemma, always chooses a lower input level to save cost, this results in low-efficiency intelligent customization.

Third, a modification mechanism for input investment decision making is proposed to enable NEE manufacturers and customers to undertake long-term cooperation on intelligent customization. The modification mechanism can improve the customized output of NEE at a lower cost while enhancing customer trust. However, the revision mechanism has an obvious effect when risk controllability is low. The improvement of customer utility is mainly affected by the reduction of risk intensity based on technological progress following intelligent customization technology breakthroughs. This means that continuous technological progress is an important driving force for NEE performance.

In conclusion, a decision-making basis is provided for realizing risk avoidance goals, eliminating the cost-benefit dilemma, and consolidating customer trust over continuous long-term cooperation in intelligent NEE customization. Although it is necessary to revise investment decisions in the short term to eliminate the impact of customization risks on the interests of customers, from a long-term strategic perspective, uncertainty is the main reason for individualized large-scale NEE production. Therefore, transforming the uncertainty of the operational environment into a value source for improving the specificity of wind power equipment and enhancing the controllability of risk factors in the context of new energy and intelligent manufacturing technology advances is the fundamental solution for increasing the sustainability of intelligent customization.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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