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Article

Research on Risk Dependency Structures and Resource Allocation Optimization in New Energy Technology Collaboration within Enterprise Distributed Innovation

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Abstract

As new energy technology systems grow increasingly complex, corporate innovation activities in photovoltaics, energy storage, wind power, and energy management exhibit distinct distributed characteristics. Cross-enterprise collaboration and cross-regional innovation have become pivotal drivers for industrial upgrading. However, the lengthy new energy industrial chain, numerous participants, and high technical coupling lead to significant knowledge stickiness in knowledge transfer processes, thereby impairing collaborative innovation efficiency. To address this issue, this paper constructs a probabilistic resource allocation optimization model for distributed innovation networks in new energy enterprises. First, Least Squares Support Vector Machine (LSSVM) is employed to predict the success rate of collaborative innovation tasks. Model parameters are jointly optimized using grid search and Particle Swarm Optimization (PSO) under RBF, Polynomial, and Sigmoid kernel functions to adapt to different types of technological coupling and knowledge stickiness structures. Subsequently, a Gaussian Copula is introduced to characterize the risk dependency structure among technological maturity, external market volatility, and R&D collaboration complexity between innovation nodes. This enables the calculation of conditional value at risk (CoVaR) to quantify collaborative innovation risks under high uncertainty in new energy technologies. During resource allocation, a cost-loss model based on Bayesian decision theory is established, and the simulated annealing algorithm is employed to solve for the optimal combination of R&D and collaborative resources. Simulation results demonstrate that under conditions of rapid new energy technology iteration and significant knowledge stickiness, this method reduces resource waste by 17%–23% compared to traditional empirical allocation approaches while enhancing cross-enterprise innovation collaboration efficiency. This study provides a quantifiable and interpretable decision-making method for distributed innovation management in the new energy industry, holding significant implications for building an efficient industrial collaborative innovation ecosystem.

Keywords: distributed innovation; new energy enterprises; knowledge stickiness; technology collaboration; LSSVM; copula; CoVaR; resource allocation optimization

1. Introduction

As new energy technology systems — including photovoltaics, wind power, and energy storage — continue to evolve, inter-enterprise technological collaboration increasingly exhibits distributed and heterogeneous characteristics. The industry innovation model has shifted from single-entity dominance to multi-node linkage mechanisms. However, against a backdrop of deepening technological coupling and heightened uncertainty, issues such as knowledge stickiness,

risk transmission, and resource misallocation have become increasingly prominent during collaboration. These challenges constrain innovation efficiency gains and the steady-state evolution of the industrial collaborative ecosystem. Addressing the urgent need to overcome structural barriers in collaborative innovation within the new energy sector, it is imperative to establish a resource allocation mechanism with dynamic responsiveness. This mechanism should enable precise identification of high-risk collaborative tasks and rational regulation of resource deployment, thereby driving the high-quality development of distributed innovation systems among enterprises.

2. Research Methods and Modeling Framework

2.1. Construction of the New Energy Distributed Innovation Network

Within the research methodology and modeling framework, constructing the distributed innovation network for new energy serves as the structural foundation for subsequent collaborative task prediction and risk dependency modeling. This requires formalizing nodes and collaborative relationships at the enterprise level. The set of enterprises participating in collaborative activities across photovoltaic, wind power, energy storage, and energy management sectors is denoted as $V = \{v_1, \dots, v_n\}$. Collaborative relationships are mapped as an undirected edge set E through three event categories: joint patents, cooperative R&D, and technology licensing. These are encoded via a weighted adjacency matrix $W = [w_{ij}]$, where edge weights are derived from the superposition of multi-source collaboration strengths:

$$w_{ij} = \alpha_1 M_{ij}^{(pat)} + \alpha_2 M_{ij}^{(rd)} + \alpha_3 M_{ij}^{(lic)}$$

where $M_{ij}^{(pat)}$, $M_{ij}^{(rd)}$, and $M_{ij}^{(lic)}$ represent the collaboration frequencies between enterprises i and j in joint patents, collaborative R&D, and technology licensing, respectively. α_1 , α_2 , and α_3 denote weight coefficients reflecting the relative importance of different collaboration types. Based on this, a time-varying network sequence $\{G_t = (V, E_t, W_t)\}$ is constructed, mapping annual collaboration information into multi-period snapshots. This provides a temporal carrier for subsequent calculations of metrics such as knowledge stickiness indices and technology maturity [1]. To visually depict the distribution of core enterprises, cross-domain coupling relationships, and collaboration intensity within the network, Figure 1 employs node size to encode enterprise collaboration levels, color to distinguish technological subfields, and edge thickness to represent collaboration strength. This forms a visual topology structure that corresponds one-to-one with matrix W . This structure serves as the foundational input feature for LSSVM collaboration task success rate prediction while also providing node-to-node relationship constraints for Gaussian Copula risk dependency modeling.

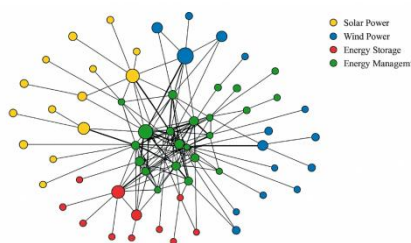


Figure 1. Schematic Diagram of the Distributed Innovation Network Structure for New Energy Enterprises.

2.2. Collaborative Innovation Task Success Rate Prediction Model (LSSVM)

After establishing the distributed innovation network structure and obtaining the collaboration intensity matrix between enterprises, it is necessary to quantitatively predict the success rate of collaborative innovation tasks for different enterprise combinations under complex technological scenarios. This provides foundational probability inputs for subsequent risk dependency structure modeling [2]. To capture the nonlinear influence of multidimensional structural factors—such as knowledge stickiness, technological distance, collaborative strength, and firm absorptive capacity—

on task success rates, a prediction model based on Least Squares Support Vector Machines (LSSVM) is constructed. Key features extracted from the network are represented as input vectors x_i , while historical collaborative task success rates are denoted as y_i . A nonlinear regression function is constructed using kernel mapping. The model's optimization objective is defined as

$$\min_{w,b,e} J(w, e) = \frac{1}{2} w^T w + \frac{\gamma}{2} \sum_{i=1}^m e_i^2, \quad s.t. y_i = w^T \phi(x_i) + b + e_i$$

where w is the feature space weight vector, ϕ is the kernel mapping function, b is the bias term, γ controls the balance between empirical and structural risk, and e_i is the error term. Considering the technological heterogeneity of new energy collaboration, three candidate kernel structures are designed: RBF, Polynomial, and Sigmoid kernels. Parameter optimization for different kernels employs a combined framework of grid search and particle swarm optimization (PSO) to ensure higher model adaptability when facing various types of technological coupling relationships [3]. Table 1 presents the key parameters and search ranges required for the three kernel types. This design provides a stable prior probability foundation for constructing conditional risk distributions in subsequent Copula models.

Table 1. LSSVM Kernel Structures and Hyperparameter Settings.

Kernel Type	Mathematical Form	Key Parameters	Search Range / Setting
RBF	$K(x_i, x_j) = \exp(-\ x_i - x_j\ ^2 / 2\sigma^2)$	σ, γ	$\sigma \in [10^{-3}, 10^2], \gamma \in [10^{-2}, 10^3]$
Polynomial	$K(x_i, x_j) = (x_i^T x_j + c)^d$	d, c, γ	$d \in \{2, 3, 4\}, c \in [0, 5]$
Sigmoid	$K(x_i, x_j) = \tanh(\kappa x_i^T x_j + \theta)$	κ, θ, γ	$\kappa \in [10^{-3}, 10], \theta \in [-5, 5]$

2.3. Risk Dependency Structure Modeling (Gaussian Copula)

After obtaining prior estimates of collaborative innovation success rates, a Gaussian Copula is introduced to construct a joint risk dependency structure among technology maturity, external market volatility, and R&D collaboration complexity, thereby capturing the interactive effects of multi-source uncertainties in new energy technology collaboration scenarios [4]. Let the marginal distributions of the three risk factors be $F_T(t)$, $F_M(m)$, and $F_C(c)$, respectively. Through probability integral transformation, we obtain uniform random variables $u_T = F_T(t)$, $u_M = F_M(m)$, and $u_C = F_C(c)$ obeying the interval $[0, 1]$. We then use the Gaussian Copula to embed them into the same correlation structure, with the joint distribution expressed as

$$C_{\Sigma}(u_T, u_M, u_C) = \Phi_{\Sigma}(\Phi^{-1}(u_T), \Phi^{-1}(u_M), \Phi^{-1}(u_C))$$

where Φ^{-1} denotes the inverse function of the standard normal distribution, and C_{Σ} represents the three-dimensional normal distribution function with correlation matrix Σ . The off-diagonal elements of Σ reflect the linear correlation and tail-end linkage strength among different risk factors. To improve modeling accuracy, this paper uses maximum likelihood estimation method to fit and modify edge distribution parameters and related structural parameters based on historical collaborative task data [5]. As shown in Figure 2, the entire Copula risk modeling module consists of an input factor layer, an edge distribution transformation layer, a Copula joint modeling core layer, and an output distribution structure layer. In this structure, the maturity of technology, market volatility, and collaborative complexity are first standardized through edge fitting and integral transformation inputs, and a joint risk distribution is constructed through Gaussian Copula. This result will serve as the input basis for the conditional risk measurement module (CoVaR calculation) and form a collaborative risk modeling loop with the LSSVM prediction module.

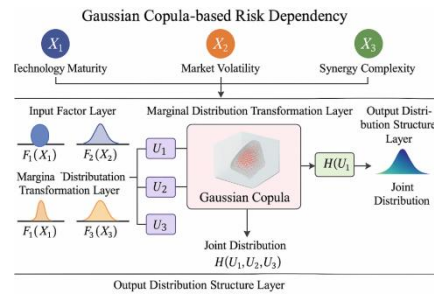


Figure 2. Gaussian Copula Risk Modeling Structure Diagram.

2.4. Collaborative Technical Risk Measurement (CoVaR)

After obtaining the joint distribution of technical maturity, market volatility, and synergistic complexity based on Gaussian Copula, it is necessary to further transform this joint uncertainty into an actionable synergistic technical risk indicator to provide constraints for subsequent resource allocation models [6]. This study adopts Conditional Value at Risk (CoVaR) as the systematic co-technical risk measurement tool. The loss variable for each new energy technology co-unit is represented as L_j . Key triggering factors (e.g., severe market volatility or high-complexity co-operation modes) are denoted as L_k . At a given confidence level α , the risk value of triggering factors is first calculated as $VaR_\alpha(L_k)$. Subsequently, the co-technical CoVaR is defined within the joint distribution described by Copula as

$$CoVaR_{\alpha,\beta}^{j|k} = \inf\{l \in R \mid Pr(L_j \leq l \mid L_k = VaR_\alpha(L_k)) \geq \beta\}$$

where β is the conditional confidence level, controlling the acceptable loss range for the collaborative technology when the trigger factor reaches extreme states. Leveraging the Copula correlation matrix constructed earlier and the task success rate distribution predicted by LSSVM, Monte Carlo sampling generates numerous scenarios within the joint risk space. This enables numerical solutions for $CoVaR_{\alpha,\beta}^{j|k}$ across different technical subdomains and collaboration modes, aggregating them into the systemic risk exposure at the collaborative task level [7]. Figure 3 organizes key risk factors, technical collaboration nodes, and their conditional excess loss probabilities into a three-tier structure: The top layer represents triggering factors (L_k), the middle layer comprises collaborative units across different technical directions (L_j), and the bottom layer consists of risk exposure metrics derived from CoVaR. Directed edges annotate conditional probabilities and threshold levels, visually illustrating the propagation paths of extreme shocks through the collaborative network along technical dimensions. This provides structured input for setting risk constraints and penalty weights in cost - loss-based probabilistic resource allocation optimization models [8].

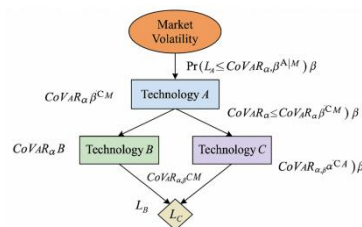


Figure 3. CoVaR-Based Collaborative Technical Risk Propagation Map.

2.5. Probabilistic Resource Allocation Optimization Model

Building upon the aforementioned collaborative innovation task success rate prediction and collaborative technology risk measurement, a probabilistic resource allocation optimization model is

designed. This formalizes the allocation problem of finite R&D and collaborative resources across multiple technological subfields and enterprise nodes as a Bayesian decision process aimed at minimizing risk-adjusted expected loss [9]. First, a prior distribution is constructed based on the success probability distribution of collaborative tasks output by LSSVM. Combining the joint risk structure and conditional risk exposure provided by Gaussian Copula and CoVaR, the success rate and loss distribution under different technology combination scenarios undergo posterior updates. This yields the conditional expected loss $E[L_i(x_i)|CoVaR_i]$ for each collaborative task at resource input level x_i . Based on this, the overall optimization objective function is formulated:

$$\min_x J(x) = \sum_{i=1}^n \pi_i E[L_i(x_i)|CoVaR_i] + \lambda \sum_{i=1}^n c_i x_i$$

where $x = (x_1, \dots, x_n)$ represents the resource allocation decision variables for each collaborative task or technology direction, π_i denotes the posterior occurrence probability updated based on observational data, c_i is the unit resource cost, λ is the decision-maker's risk aversion coefficient, and total budget and resource capacity constraints are imposed to define the feasible domain. Given the objective function's pronounced non-convexity in high-dimensional space, a simulated annealing algorithm is employed to control the temperature and design perturbation acceptance for x 's search trajectory. By adopting a "probabilistic acceptance of suboptimal solutions" approach, it avoids getting stuck in local optima, achieving a dynamic trade-off between enhancing success rates and reducing risk exposure in resource combinations [10].

3. Simulation Design and Results Analysis

3.1. Experimental Setup and Parameter Configuration

To validate the adaptability and stability of the probabilistic resource allocation optimization model in multi-technology collaboration scenarios, this study designed a simulation testing platform covering three technology domains: wind power, photovoltaics, and energy storage. A multi-stage collaborative task set was constructed as the experimental subject. The experiments drew upon 118 valid collaborative task samples extracted from domestic renewable energy enterprises' joint patents and cooperative R&D projects between 2017 and 2024. An initial adjacency matrix was constructed based on enterprise collaboration frequency and technological heterogeneity to input the network module. The LSSVM module employed a 7:3 training-to-validation split ratio, with a fixed RBF kernel structure. The particle swarm optimization algorithm ran for 300 iterations with a population size of 30, using an initial inertia factor of 0.8 that decreased progressively across generations. In risk dependency modeling, three types of marginal distributions were fitted using a mixture of extreme value and normal distributions. The correlation matrix generated 1,000 joint samples via Monte Carlo sampling for CoVaR estimation. For resource allocation optimization, the total budget is set to 1, decision variables $x \in [0,1]^n$, with an initial temperature $T_0 = 100$ and cooling rate $\alpha = 0.92$. A dynamic adjustment mechanism for the acceptance probability of perturbations per iteration is implemented. Key parameters for each module are shown in Table 1, providing a unified configuration basis for subsequent multi-strategy comparative analysis.

Table 1. Key Parameter Settings and Adaptive Strategies for Each Module.

Module Stage	Parameter Name	Value/Setting Method	Adaptation Logic Description
LSSVM Training Module	Kernel Function Type	RBF	Nonlinear Collaborative Structure Modeling Oriented

	Particle Swarm Population Size	30	Ensuring Global Optimization Capability
	Maximum Iteration Count	300	Control convergence stability
Copula Modeling Module	Sample Generation Method	Monte Carlo (N=1000)	Constructing Joint Risk Distributions
	Marginal Distribution Fitting	EVT / GMM Hybrid	Capturing Tail Correlation Characteristics
Simulated Annealing Resource Allocation Module	Initial Temperature T0	100	Initiate Wide-Area Search
	Cooling Rate α	0.92	Control temperature decay rate
	Perturbation acceptance mechanism	Metropolis criterion + dynamic update	Preventing Local Optima Trapping

3.2. Results Analysis and Discussion

Based on the aforementioned simulation environment and parameter settings, this study compares the proposed probabilistic optimization model with traditional empirical allocation strategies from the perspective of resource allocation structure evolution. It analyzes performance differences in collaborative task success rates and risk exposure levels. Three typical technology combinations—photovoltaic (PV), wind power, and energy storage—were selected. Under fixed total resource constraints, five rounds of resource allocation simulations were conducted using both the empirical method (allocation based on collaboration frequency ratios) and the optimized model (incorporating LSSVM + CoVaR structure). As shown in Figure 4, the three-dimensional resource allocation evolution diagram depicts task indices and technology directions along the X and Y axes, respectively, with the Z axis representing corresponding resource allocation ratios. Color gradients indicate task success rates under each configuration. The figure reveals that the resource distribution generated by the optimization model concentrates more heavily in high CoVaR exposure regions, significantly mitigating the resource wastage observed in low-success-rate tasks under the empirical method. Particularly in the wind-storage coupling task, resource reallocation concentrated the success rate improvement range between 0.12 and 0.18, whereas the empirical configuration spread widely across 0.06 to 0.11—a 54% difference. This contrast not only validates the model's ability to identify and respond to high-risk tasks but also provides data support for subsequent strategy adjustment mechanisms under multi-period dynamic resource deployment.

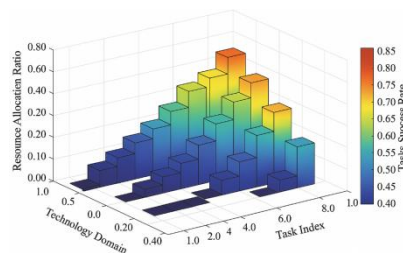


Figure 4. Multidimensional Resource Allocation Mapping and Task Success Response Structure.

4. Conclusions

In multi-source heterogeneous technical collaboration environments, the integrated prediction and measurement framework combining LSSVM and Copula structures effectively captures knowledge stickiness and risk dependency characteristics in distributed renewable energy innovation. This establishes a probabilistic resource allocation optimization model with decision interpretability. By employing risk-adjusted expected loss minimization within a Bayesian framework, it expands quantitative pathways for collaborative task resource deployment. Although simulation experiments validate the model's effectiveness, its robustness in handling extreme mutation scenarios remains limited by constraints in collaborative data acquisition dimensions and task diversity characterization methods. Future work may integrate graph neural networks with dynamic game mechanisms to further optimize collaborative network evolution modeling and resource reallocation strategies, thereby enhancing dynamic prediction and strategic response capabilities for technological collaboration within complex industrial ecosystems.

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