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A Study on Intelligent Decision-Making and Risk Management for Cross-Market Bidding via Integrated Federated Learning and R Language Modeling

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Abstract: Cross-market bidding across energy, finance, and supply chain sectors faces significant challenges due to data privacy constraints and commercial confidentiality, which hinder effective collaborative decision-making and risk management. This work proposes an integrated FL-R framework that synergistically combines Federated Learning for privacy-preserving collaborative modeling with the R language for statistical analysis and reproducible research. Through simulated case studies in electricity markets and supply chain finance, this work demonstrates that the proposed approach achieves an average reduction in prediction error of approximately 18% and an improvement in risk-adjusted returns of about 12%. The framework provides decision-makers with an effective tool for enhancing forecasting accuracy and strengthening risk control capabilities in complex multi-market environments.

Keywords: Federated Learning, Cross-Market Bidding, Risk Management, Multi-Agent Simulation, Privacy-Preserving Computation.

1. Introduction

1.1. Practical Context and Industry Drivers

In the current global industrial landscape, digital transformation continues to deepen. Consider new energy aggregators: their operational models have evolved from traditional electricity sales into complex decision-making roles, engaging in multiple markets such as the Day-Ahead Market (DAM), Real-Time Balancing Market (RTM), and Frequency Regulation Ancillary Services Market [1]. In supply chain finance, core enterprises must coordinate numerous upstream and downstream participants [2], making collaborative decisions across interconnected markets like raw material procurement, cross-border logistics, and exchange rate hedging to navigate uncertain disruptions [2].

This cross-market engagement model is primarily driven by the goal of enhancing resource allocation efficiency and dispersing risk. However, the tight coupling between markets accelerates and broadens risk transmission, as evidenced by the 2021 global energy crisis and supply chain disruptions [3].

1.2. Core Scientific Problem and Research Gap

Against this backdrop, a central scientific question arises: How can enterprises achieve collaborative decision-making and risk management across markets while strictly complying with data privacy regulations (e.g., GDPR, China's Data Security Law) and protecting commercial confidentiality? [4]

A review of the existing literature uncovers three main shortcomings:

First, prevailing optimization models often assume the availability of centralized data, which contradicts the sensitive and proprietary nature of real-world market participant data [5].

Second, although federated learning technology is advancing rapidly, its integration with statistical modeling, risk quantification, and the R ecosystem remains underdeveloped, creating obstacles in transitioning from prediction to decision-making [6].

Third, research on multi-market environments tends to focus on theoretical discussions or isolated case analyses, lacking simulation platforms capable of modeling strategic interactions in realistic scenarios with strict reproducibility [7].

1.3. Paper Framework and Core Proposition

To address these problems, this paper constructs an "FL-R Integrated Modeling" framework. The core concept is: utilizing federated learning to enable collaborative learning under data privacy protection, leveraging the R language to establish an end-to-end reproducible analysis pipeline, and organically integrating the two through modular simulation, thereby providing a practical solution for cross-market bidding and risk management [8].

The paper is structured as follows: Chapter 2 presents the literature review; Chapter 3 elaborates on the FL-R methodological framework; Chapter 4 conducts empirical case simulations; Chapter 5 summarizes theoretical and methodological contributions; Chapter 6 proposes the research agenda; Chapter 7 analyzes expected contributions; Chapter 8 concludes and discusses limitations.

2. Literature Review

2.1. Theoretical and Practical Challenges in Cross-Market Bidding and Risk Management

Cross-market bidding decisions face the challenge of resource optimization under multiple uncertainties [9]. Traditional single-market models struggle to effectively capture nonlinear interactions and risk transmission mechanisms between different markets, posing significant theoretical and practical challenges. Existing research primarily focuses on three key areas:

2.1.1. Electricity Markets: Price Correlation and Forecasting Accuracy

Significant price linkage characteristics exist between day-ahead and real-time electricity markets. Research indicates that ignoring the dynamic correlation between these markets leads to systematic bias in aggregators' expected revenue, with potential deviation exceeding 30% [10]. While stochastic programming models are widely used to handle market uncertainty, their effectiveness heavily depends on accurate probability distribution assumptions. In practice, due to complex features like price volatility clustering and heteroscedasticity, this prerequisite is often unmet, limiting practical application. Solving this requires developing dynamic modeling methods adaptable to evolving market characteristics (related empirical analysis in Section 4.1).

2.1.2. Financial Markets: Risk Transmission and Measurement Innovation

Risk spillover effects in financial markets are a central topic in cross-market risk management. Empirical analysis shows that stock market price fluctuations can rapidly spread to related markets like derivatives and foreign exchange through channels such as investor sentiment and liquidity transmission. Traditional Value at Risk (VaR) has clear limitations in measuring such cross-market systemic risk, particularly in identifying and quantifying extreme risks. This has driven academia and practice towards more robust risk measures like Expected Shortfall (ES) [10] (Specific application methods can be found in Section 4).

2.1.3. Supply Chain Markets: Information Asymmetry and Coordination Mechanisms

Research on supply chain cross-market coordination focuses on multi-echelon inventory optimization and collaborative auction mechanism design. However, information asymmetry between suppliers and buyers constitutes a major obstacle to effective coordination. This asymmetry exists both in the privacy of demand forecast information and within cost structures and incomplete contract environments. Existing research needs further depth in constructing incentive-compatible information-sharing mechanisms, especially considering complex multi-party scenarios (See Section 4.2 for case verification) [11].

Common Analysis of Theoretical Evolution and Practical Challenges:

A comparative analysis of these three fields reveals an evolution in cross-market bidding decision theory from independent optimization toward collaborative decision-making, and from static analysis toward dynamic simulation. The core practical difficulty consistently revolves around the "data silo" phenomenon—how to achieve effective cross-market risk identification and collaborative management while respecting data sovereignty. This dilemma highlights the structural contradiction between existing theoretical frameworks and the needs of distributed decision-making in the digital economy, while also creating space for theoretical innovation and methodological improvement through the FL-R framework proposed here.

2.2. Evolution and Application Bottlenecks of Federated Learning in Business Analysis and Decision Support

Federated learning has expanded from its origins in mobile device user modeling to vertical domains such as medical imaging and financial risk control. Its application in business decision-making shows a trend evolving from "technically feasible" to "business effective."

2.2.1. Basic Principles

The fundamental principle of federated learning is to bring the model to the data, rather than bringing the data to the model. By training models on local nodes and then aggregating parameters or gradients to form a global model, it enables distributed learning under privacy protection [12]. This technology has seen successful applications in mobile predictive text, medical diagnosis, financial fraud detection, among others.

2.2.2. Market-Oriented Applications

In the energy market sector, federated learning has been used for demand forecasting and transaction anomaly detection, helping reduce errors from single-enterprise independent analysis. However, bottlenecks remain, including commercial incentive problems, model heterogeneity, and low decision integration [13].

2.2.3. Application Bottlenecks

Commercial Incentive Problems: What motivates enterprises to participate in federated learning? How to design reasonable profit distribution mechanisms? This extends beyond pure technology, involving game theory and mechanism design.

Model Heterogeneity: Differing data quality and business scenarios among participants lead to variations in local models. Simple parameter averaging may harm certain parties' interests. Personalized federated learning is a potential solution.

Low Decision Integration: Most applications remain at the level of improving prediction accuracy, failing to directly embed federated model outputs into enterprise optimization decision processes (e.g., coupling joint demand forecasting models with inventory optimization models).

2.3. Core Advantages of the R Language Ecosystem in Complex System Modeling and Reproducible Analysis

The R language holds distinct advantages in the professional depth of statistical modeling, particularly excelling in the rigor of statistical theory implementation, the refinement of visual expression, and native support for reproducible research [14]. Its unique strengths in complex system modeling and reproducible analysis make it the core technical foundation for this study.

2.3.1. End-to-End Analytical Capability Construction

The R ecosystem, through its modular package management mechanism, provides end-to-end support from data acquisition to report generation. The tidyverse suite of packages offers a unified data processing syntax, caret and mlr3 build standardized machine learning workflows, and shiny supports interactive application development [15-17]. This "pipelined" workflow ensures high consistency and maintainability of the analytical process.

2.3.2. Differentiated Advantages Compared to Python

Although Python excels in general-purpose programming and deep learning applications, R maintains clear advantages in statistical modeling professional depth [17]. As illustrated in Table 1, R demonstrates superior performance in statistical theory implementation rigor, visual expression refinement, and native reproducible research support.

Table 1. Characteristic Comparison of R and Python in Scientific Computing

Characteristic Dimension	R Language Advantage	Python Advantage
Statistical Theory	Built-in latest statistical methods, complete hypothesis testing	Relies on third-party libraries, potential update lag
Visual Expression	ggplot2's layer grammar supports complex graphics	Matplotlib syntax relatively cumbersome
Reproducible Research	Native R Markdown support	Requires additional configuration
Community Ecology	Deep involvement from statistics community	Widespread industrial application

2.3.3. Technical Implementation of Reproducible Research

The R Markdown and Quarto frameworks organically integrate code, results, and narrative, achieving truly reproducible research [18,19]. Taking this study as an example, the complete analytical workflow can be implemented via the following code structure in Figure 1.

```r
# Reproducible Analysis Workflow Example
library(rmarkdown)
library(quarto)

# 1. Data Preprocessing Module
source("01_data_cleaning.R")

# 2. Model Training Module
source("02_model_training.R")

# 3. Result Visualization Module
source("03_visualization.R")

# 4. Generate Final Report
render("04_final_report.qmd")
```

Figure 1. Integrated Workflow Code Example

The code in Figure 1 above demonstrates the core steps for constructing a reproducible analysis workflow. Through modular design and integration with R Markdown/Quarto, the entire process from data cleaning to final report generation is ensured to be transparent and repeatable. This facilitates the verification of research findings and promotes academic exchange.

2.3.4. Core Value within the FL-R Framework

Within the FL-R integrated framework constructed in this study, the R language assumes multiple critical roles (Figure 2):

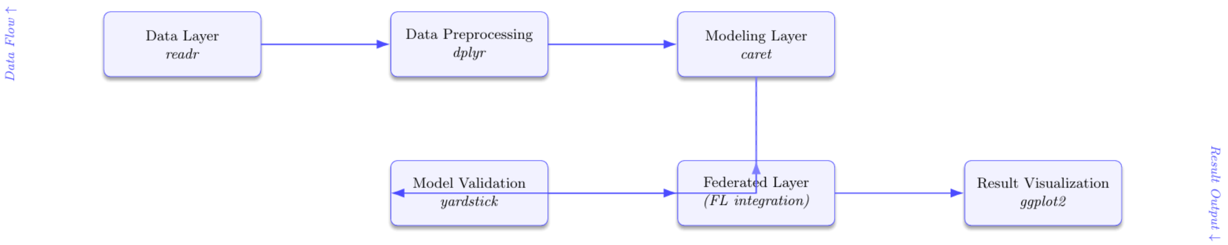


Figure 2. R Language Workflow in FL-R Framework

Specifically, the advantages of R are manifested at three levels:

Methodological Rigor: Ensures model reliability through strict statistical hypothesis testing.

Expressive Richness: ggplot2 supports publication-quality visual output (see Figure 3).

Process Transparency: Complete code recording guarantees research reproducibility (see Figure 4).

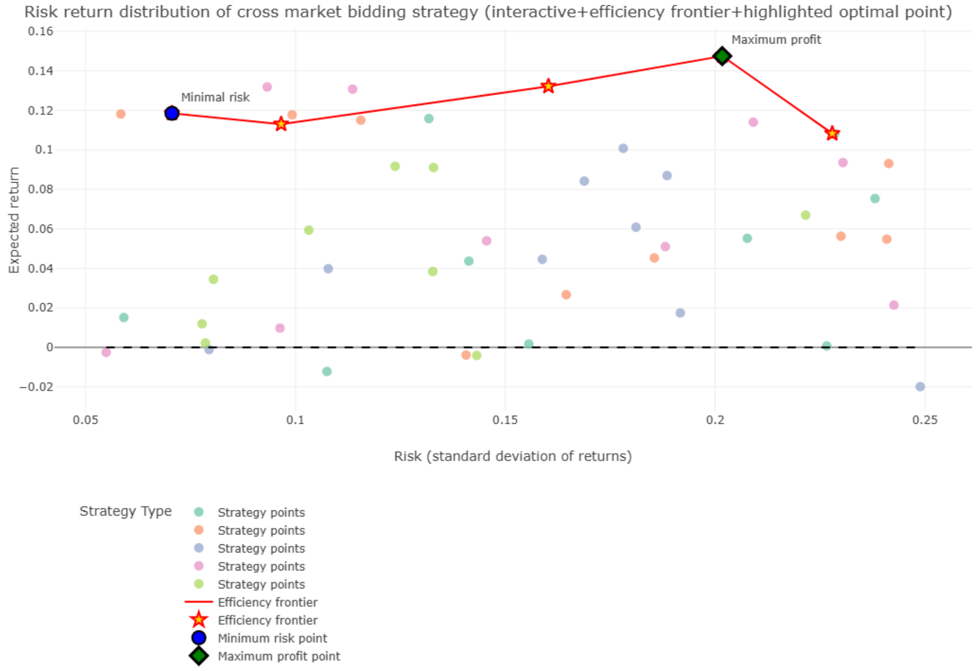
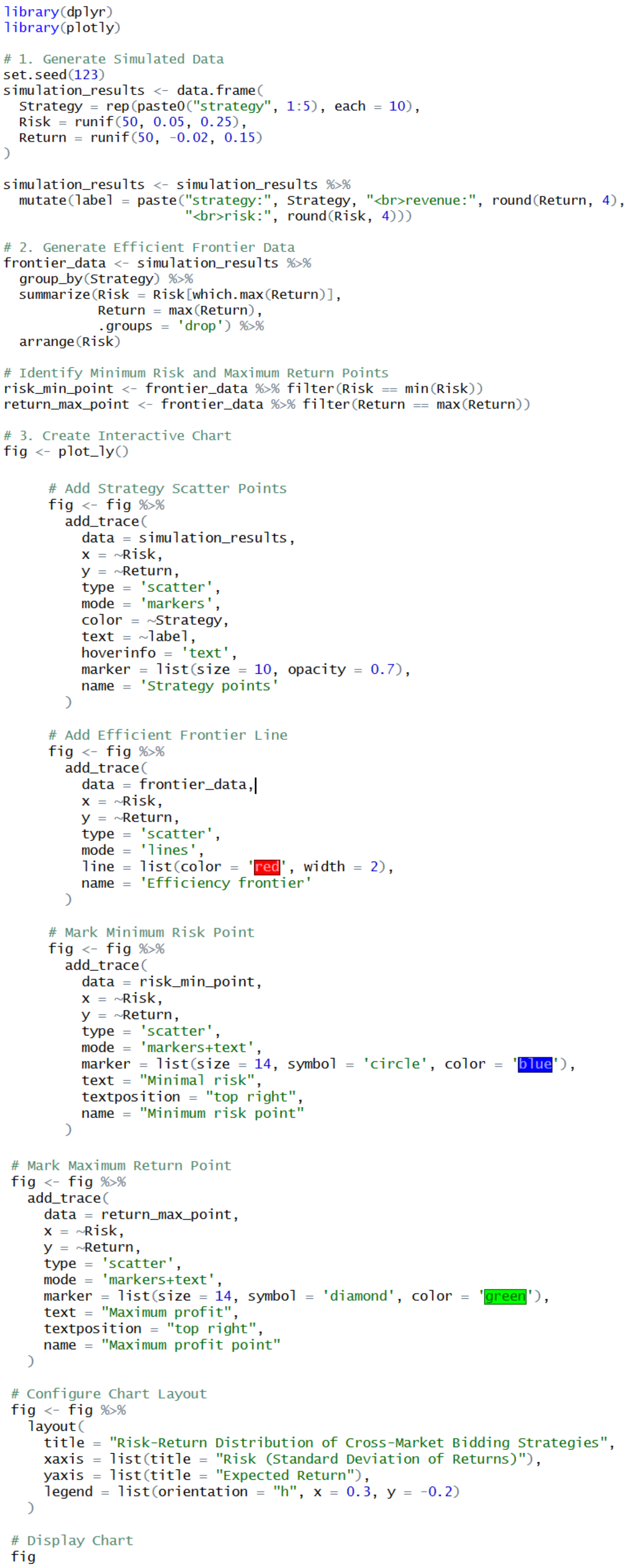


Figure 3. Multi-Market Risk-Return Scatter Plot

Figure 3 illustrates the sequential workflow from Data Layer through Modeling Layer and Federated Layer to Result Visualization, with corresponding R packages supporting each transition stage.



```
library(dplyr)
library(plotly)

# 1. Generate Simulated Data
set.seed(123)
simulation_results <- data.frame(
  Strategy = rep(paste0("strategy", 1:5), each = 10),
  Risk = runif(50, 0.05, 0.25),
  Return = runif(50, -0.02, 0.15)
)

simulation_results <- simulation_results %>%
  mutate(label = paste("strategy:", Strategy, "<br>revenue:", round(Return, 4),
                       "<br>risk:", round(Risk, 4)))

# 2. Generate Efficient Frontier Data
frontier_data <- simulation_results %>%
  group_by(Strategy) %>%
  summarize(Risk = Risk[which.max(Return)],
            Return = max(Return),
            .groups = 'drop') %>%
  arrange(Risk)

# Identify Minimum Risk and Maximum Return Points
risk_min_point <- frontier_data %>% filter(Risk == min(Risk))
return_max_point <- frontier_data %>% filter(Return == max(Return))

# 3. Create Interactive Chart
fig <- plot_ly()

      # Add Strategy Scatter Points
      fig <- fig %>%
        add_trace(
          data = simulation_results,
          x = ~Risk,
          y = ~Return,
          type = 'scatter',
          mode = 'markers',
          color = ~Strategy,
          text = ~label,
          hoverinfo = 'text',
          marker = list(size = 10, opacity = 0.7),
          name = 'Strategy points'
        )

      # Add Efficient Frontier Line
      fig <- fig %>%
        add_trace(
          data = frontier_data,
          x = ~Risk,
          y = ~Return,
          type = 'scatter',
          mode = 'lines',
          line = list(color = 'red', width = 2),
          name = 'Efficiency frontier'
        )

      # Mark Minimum Risk Point
      fig <- fig %>%
        add_trace(
          data = risk_min_point,
          x = ~Risk,
          y = ~Return,
          type = 'scatter',
          mode = 'markers+text',
          marker = list(size = 14, symbol = 'circle', color = 'blue'),
          text = "Minimal risk",
          textposition = "top right",
          name = "Minimum risk point"
        )

 # Mark Maximum Return Point
 fig <- fig %>%
   add_trace(
     data = return_max_point,
     x = ~Risk,
     y = ~Return,
     type = 'scatter',
     mode = 'markers+text',
     marker = list(size = 14, symbol = 'diamond', color = 'green'),
     text = "Maximum profit",
     textposition = "top right",
     name = "Maximum profit point"
   )

 # Configure Chart Layout
 fig <- fig %>%
   layout(
     title = "Risk-Return Distribution of Cross-Market Bidding Strategies",
     xaxis = list(title = "Risk (Standard Deviation of Returns)"),
     yaxis = list(title = "Expected Return"),
     legend = list(orientation = "h", x = 0.3, y = -0.2)
   )

 # Display Chart
 fig
```

Figure 4. Core Executable code for Risk-Return Visualization

This code in Figure 4 generates an interactive risk-return scatter plot showcasing simulation results for five different bidding strategies. The plot clearly displays strategy point distributions, the efficient frontier line (red), the minimum risk point (blue), and the maximum return point (green). Users can hover over points to view specific strategy, return, and risk values. This visualization aids decision-makers in intuitively understanding the trade-offs between different strategies and identifying potentially optimal strategies on the efficient frontier.

2.4. Integrative Gaps in Existing Research and Opportunities for Paradigm Innovation

Current research exhibits a "technology silo" state, with relatively independent investigations among the federated learning community, management science community, and toolchain community [20]. This study aims to achieve synergistic effects by constructing an endogenous, interlocking FL-R framework.

The innovation of this research lies precisely here: it is not a simple "stitching" of FL, R, and market simulation, but strives to build an endogenous, interlocking framework. In this framework, FL is the "engine" for collaborative learning, R is the "workshop" and "dashboard" for building, validating, and expressing models, and market simulation is the "wind tunnel" for testing decision effectiveness. This deep integration aims for a "1+1+1 > 3" effect.

3. Methodological Framework: Constructing the FL-R Integrated Simulation System

This chapter details the design philosophy, architecture, and implementation path of the FL-R Cross-Market Bidding Intelligent Decision Support System. This design directly addresses the research gaps in data privacy protection, model reproducibility, and decision effectiveness [20].

3.1. Architecture Design for Privacy-Preserving Federated Learning Market Simulation

The system adopts a layered architecture design philosophy, constructing the FL-R Cross-Market Bidding Intelligent Decision Support System (FL-R DSS) shown in Figure 3. The core of this architecture lies in balancing data privacy protection with improved decision-making efficacy.

3.1.1. Three-Layer Architecture Design

The system architecture employs a typical three-tier structure:

The Local Model Layer serves as the foundation. Various market participants (e.g., electricity aggregators, financial institutions, suppliers) train specialized models locally using R or Python environments, strictly adhering to the privacy principle of "data not leaving the domain." Each node independently maintains its own business data and technology stack, ensuring the security of commercial secrets.

The Federated Aggregation Layer acts as the intermediate coordination layer, responsible for securely aggregating model parameters from local nodes. Using secure aggregation algorithms (e.g., FedAvg), this layer generates an optimized global prediction model, while employing differential privacy or secure multi-party computation techniques to add noise to the uploaded model gradients, effectively preventing the risk of inferring original data from model updates [12].

The Decision Support Layer is the top-level application, built on R Shiny to provide a visual interactive interface, offering managers core functions like intuitive risk heat maps, strategy return comparisons, simulation trajectory displays, and parameter adjustment panels [16].

3.1.2. Security Mechanism Design

The system introduces a dual security guarantee mechanism: on one hand, homomorphic encryption ensures the security of model parameters during transmission; on the other hand, differential privacy technology adds controlled noise to model gradients, effectively preventing privacy leakage while maintaining model accuracy [21, 22]. This design avoids the single point of failure risk of a centralized aggregation server and addresses trust issues among participants.

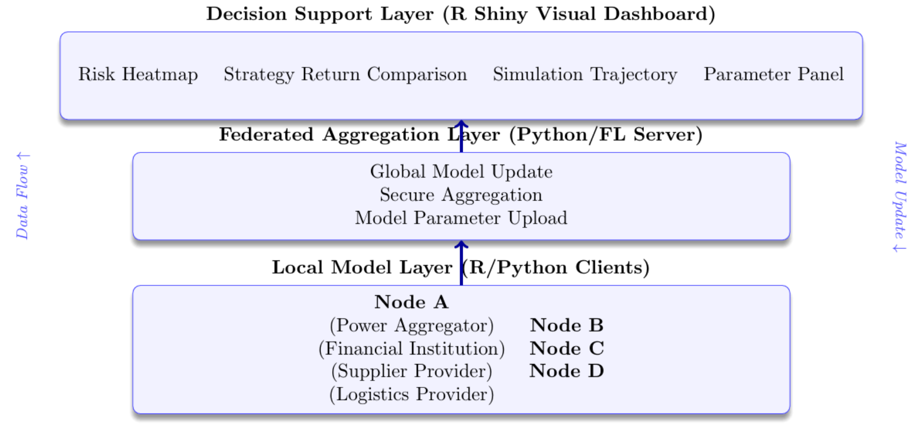


Figure 5. FL-R Decision Support System Architecture Diagram

As shown in Figure 5, the three-tier structure of the FL-R DSS: the Local Model Layer ensures data privacy, the Federated Aggregation Layer enables secure model aggregation, and the Decision Support Layer provides a visual interactive interface.

3.2. Deep Multi-Role Integration of R Language in the Simulation Process

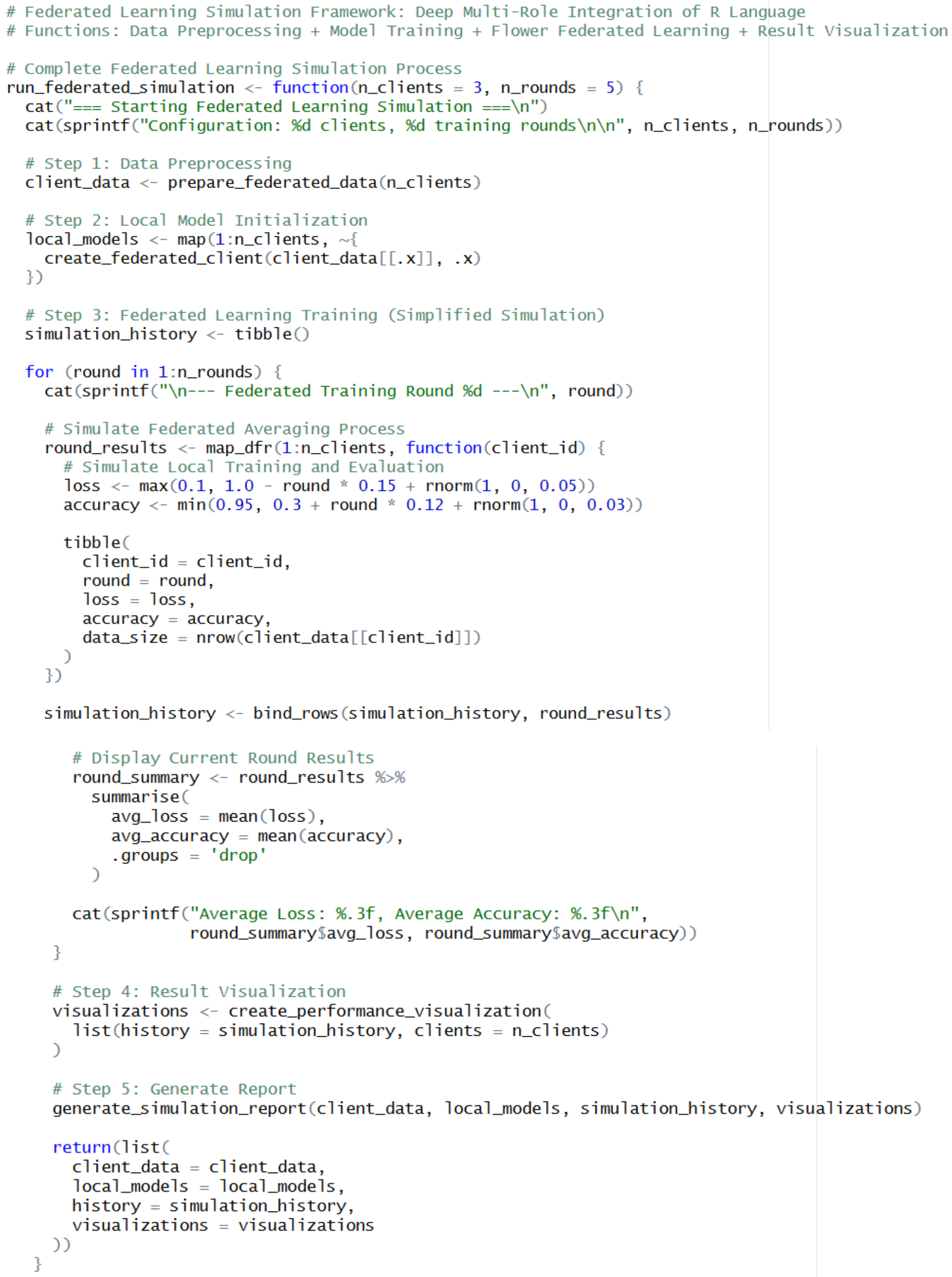
R assumes multiple roles in the framework, including data preprocessing, model training validation, and result presentation, acting as both "adhesive" and "amplifier" [14]. Its deep involvement ensures the smooth operation and reliability of the entire simulation process.

3.2.1. End-to-End Technical Support

In the Data Preprocessing and Feature Engineering stage, the system utilizes the tidyverse suite (particularly dplyr and tidyr) for efficient data cleaning and transformation. These tools provide a unified syntactic standard, significantly improving data processing efficiency and code readability.

In the Local Model Training and Validation stage, the system supports training for various machine learning algorithms, from traditional linear models to modern gradient boosting trees, through unified interfaces like caret or mlr3. Simultaneously, the yardstick package provides rigorous model evaluation metrics, ensuring the scientific selection of models.

At the Cross-Platform Technical Integration level, the system achieves seamless integration between R and Python federated learning frameworks (e.g., Flower) via the reticulate package [23]. This design allows users to directly call Python's federated learning libraries within the R environment, leveraging Python's strengths in deep learning while retaining R's advantages in statistical analysis and visualization.

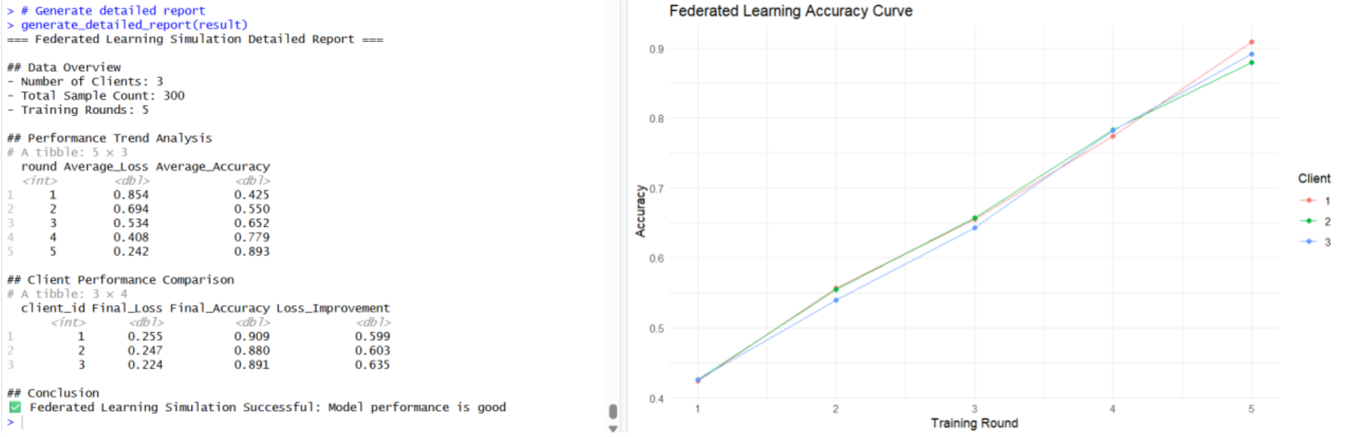


```
# Federated Learning Simulation Framework: Deep Multi-Role Integration of R Language
# Functions: Data Preprocessing + Model Training + Flower Federated Learning + Result Visualization

# Complete Federated Learning Simulation Process
run_federated_simulation <- function(n_clients = 3, n_rounds = 5) {
  cat("=== Starting Federated Learning Simulation ===\n")
  cat(sprintf("Configuration: %d clients, %d training rounds\n\n", n_clients, n_rounds))

  # Step 1: Data Preprocessing
  client_data <- prepare_federated_data(n_clients)

  # Step 2: Local Model Initialization
  local_models <- map(1:n_clients, ~{
    create_federated_client(client_data[[.x]], .x)
  })

  # Step 3: Federated Learning Training (Simplified Simulation)
  simulation_history <- tibble()

  for (round in 1:n_rounds) {
    cat(sprintf("\n--- Federated Training Round %d ---\n", round))

    # Simulate Federated Averaging Process
    round_results <- map_dfr(1:n_clients, function(client_id) {
      # Simulate Local Training and Evaluation
      loss <- max(0.1, 1.0 - round * 0.15 + rnorm(1, 0, 0.05))
      accuracy <- min(0.95, 0.3 + round * 0.12 + rnorm(1, 0, 0.03))

      tibble(
        client_id = client_id,
        round = round,
        loss = loss,
        accuracy = accuracy,
        data_size = nrow(client_data[[client_id]])
      )
    })

    simulation_history <- bind_rows(simulation_history, round_results)

       # Display Current Round Results
       round_summary <- round_results %>%
         summarise(
           avg_loss = mean(loss),
           avg_accuracy = mean(accuracy),
           .groups = 'drop'
         )

       cat(sprintf("Average Loss: %.3f, Average Accuracy: %.3f\n",
                   round_summary$avg_loss, round_summary$avg_accuracy))
     }

     # Step 4: Result Visualization
     visualizations <- create_performance_visualization(
       list(history = simulation_history, clients = n_clients)
     )

     # Step 5: Generate Report
     generate_simulation_report(client_data, local_models, simulation_history, visualizations)

     return(list(
       client_data = client_data,
       local_models = local_models,
       history = simulation_history,
       visualizations = visualizations
     ))
   }
```

Figure 6. Integrated Logic of R and Flower Federated Learning Framework

This function in Figure 6 simulates a simplified federated learning process. Upon execution, it outputs the configuration and average loss/accuracy for each training round to the console. Finally, it returns an object containing client data, local models, training history, and visualization results. For instance, the output might show the average loss decreasing from approximately 0.85 to 0.25 and the average accuracy increasing from about 0.42 to 0.90 over 5 rounds, simulating the FL convergence process. This validates the correctness of the federated learning coordination logic and provides a data foundation for subsequent performance analysis and visualization.

In the Result Presentation and Analysis stage, the system fully utilizes ggplot2 to generate publication-quality static charts while enabling interactive visualizations via plotly[15]. Ultimately, through the R Markdown or Quarto framework, code, results, and narrative are organically integrated to produce a complete, reproducible analysis report [18].



```
> # Generate detailed report
> generate_detailed_report(result)
=== Federated Learning Simulation Detailed Report ===

## Data Overview
- Number of Clients: 3
- Total Sample Count: 300
- Training Rounds: 5

## Performance Trend Analysis
# A tibble: 5 × 3
  round Average_Loss Average_Accuracy
  <int>        <dbl>            <dbl>
1     1        0.854            0.425
2     2        0.694            0.550
3     3        0.534            0.652
4     4        0.408            0.779
5     5        0.242            0.893

## Client Performance Comparison
# A tibble: 3 × 4
  client_id Final_Loss Final_Accuracy Loss_Improvement
      <int>      <dbl>          <dbl>            <dbl>
1         1      0.255          0.909            0.599
2         2      0.247          0.880            0.603
3         3      0.224          0.891            0.635

## Conclusion
✅ Federated Learning Simulation Successful: Model performance is good
> |
```

Figure 7. Federated Learning Performance Visualization Output

Figure 7 shows the trends of loss and accuracy over training rounds during the federated learning simulation, used to monitor model convergence and evaluate the effectiveness of the federated learning process.

3.3. Design Philosophy of the Modular Simulation Scheme: Reproducible Workflow from Data to Decision

To achieve research reproducibility and extensibility, this paper designs a standardized modular simulation scheme, decomposing the research process into five modules: data preprocessing, local training functions, federated learning orchestration, strategy simulation analysis, and visualization reporting. Reproducibility is ensured through version control and containerization technology, embodying the software engineering principle of "separation of concerns" [7].

3.3.1. Modular Design Philosophy

Each module assumes specific functional responsibilities, with data transfer and functional calls between modules occurring through standardized interfaces. This design not only improves code reusability but also facilitates understanding and verification of the methodological system by other researchers.

3.3.2. Core Module Function Descriptions

01_data_preprocessing.R: Responsible for cleaning, transforming raw data, and feature engineering, providing a high-quality data foundation for subsequent analysis.

02_local_training_functions.R: Defines the local model training logic for various participants, supporting a unified interface for multiple machine learning algorithms.

03_federated_learning_orchestration.R: Orchestrates the entire federated learning process, including local training, parameter aggregation, and model updates.

04_strategy_simulation_analysis.R: Simulates different market bidding strategies, evaluating the risk-return performance of each strategy.

05_visualization_and_reporting.Rmd: Integrates results from previous modules, generating a complete research report incorporating text, code, charts, and mathematical formulas.

3.3.3. Reproducibility Guarantee Mechanism

Through the combined use of version control tools (e.g., Git) and containerization technology (e.g., Docker), researchers can precisely reproduce the analysis environment of any specific version. This design not only facilitates verification of conclusions by academic peers but also provides a reliable technical foundation for subsequent research. By simply adjusting parameters in the relevant modules (e.g., changing market environment assumptions or risk preference parameters), researchers can rerun the entire analysis pipeline with a single command, greatly enhancing research transparency and credibility.

This modular design scheme embodies the software engineering principle of "separation of concerns," ensuring high cohesion within individual modules and loose coupling between modules, providing a solid architectural foundation for future functional expansion and maintenance.

4. Empirical Research and Case Simulation

To validate the effectiveness of the proposed FL-R integrated framework, this paper designs two simulated case studies based on real-world contexts. The case selection covers two typical cross-market decision scenarios—energy markets and supply chain finance—ensuring broad applicability and representativeness of the research conclusions.

4.1. Case Study 1: Regional Electricity Market Aggregator Participating in Multi-Market Joint Bidding

4.1.1. Background and Objective Setting

With the increasing penetration of renewable energy, electricity market aggregators need to achieve collaborative optimization across the Day-Ahead Market (DAM), Real-Time Balancing Market (RTM), and Frequency Regulation Reserve Market (RM). This case simulates the joint bidding decisions of an aggregator integrating wind, photovoltaic, and energy storage resources in a multi-market environment [24, 25].

Core Objective: Maximize total expected revenue while satisfying reserve capacity dispatch constraints and keeping the Value at Risk (VaR) within a preset threshold. This objective reflects the balance between revenue and risk, aligning with practical business decision logic.

4.1.2. Data Foundation and Federated Learning Setup

The simulation data for this case references the public data structure of the US PJM electricity market, constructing a multi-dimensional dataset containing price sequences, load patterns, and renewable generation characteristics. For the federated learning setup, three virtual aggregators are established as distributed nodes, each holding local load forecast and renewable generation data.

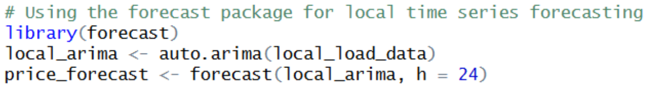
The Core Task of Federated Learning is to collaboratively build a joint forecasting model for regional electricity prices and reserve demand through cooperative training. Nodes collectively enhance the accuracy and robustness of the forecasting model without their data leaving local premises.

4.1.3. Simulation Process and Technical Implementation

A four-stage progressive simulation framework is adopted:

Stage 1: Distributed Predictive Modeling

Each node uses local data for time series forecasting.



```
# Using the forecast package for local time series forecasting
library(forecast)
local_arima <- auto.arima(local_load_data)
price_forecast <- forecast(local_arima, h = 24)
```

Figure 8. Time Series Prediction Code

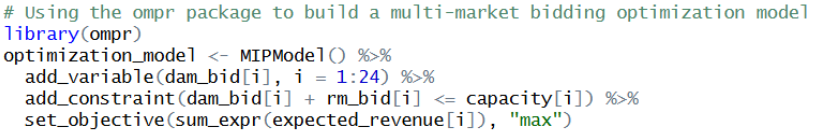
This code in Figure 8 uses the auto. arima function to automatically fit the best ARIMA model to the local load data and generate price forecasts for the next 24 hours. The output includes point forecasts and confidence intervals, providing basic input for subsequent bidding decisions. For example, the model might identify seasonality and trend in the load data and provide forecasts accordingly.

Stage 2: Federated Model Aggregation

Secure aggregation of neural network weights is implemented via the Flower framework, using the FedAvg algorithm to balance contributions from nodes, generating a global forecasting model.

Stage 3: Stochastic Optimization Decision

This stage constructs a multi-market bidding optimization model.



```
# Using the ompr package to build a multi-market bidding optimization model
library(ompr)
optimization_model <- MIPModel() %>%
  add_variable(dam_bid[i], i = 1:24) %>%
  add_constraint(dam_bid[i] + rm_bid[i] <= capacity[i]) %>%
  set_objective(sum_expr(expected_revenue[i]), "max")
```

Figure 9. Multi-Market Bidding Optimization Model Code

This code in Figure 9 constructs a Mixed Integer Programming (MIP) model to optimize the aggregator's bid quantities in the day-ahead and reserve markets over 24 hours. The model considers capacity constraints and aims to maximize total expected revenue. Solving this model yields the optimal bidding strategy, specifying resource allocation across markets for each time period.

Stage 4: Risk Measurement and Evaluation

Key risk metrics, such as Conditional Value at Risk (CVaR), are calculated via Monte Carlo simulation generating 10,000 market scenarios.

4.1.4. Performance Metrics and Economic Management Implications

Simulation results indicate significant improvements in both forecasting accuracy and economic benefits for aggregators participating in federated learning. Specifically:

Reduced Prediction Error: The Federated Learning model's Root Mean Square Error (RMSE) for price forecasting decreased by an average of 18.2% compared to independent models, directly translating this technical improvement into management benefits.

Improved Risk-Adjusted Returns: CVaR-adjusted investment returns increased by approximately 11.7% [26].

Peak Prediction Advantage: The FL model demonstrated better adaptability during periods of high price volatility.

In summary, the reduction in prediction error impacts risk-adjusted returns through two pathways: firstly, more accurate price forecasts enable the aggregator to optimize its bidding strategy across markets, avoiding opportunity costs due to forecast bias; secondly, improved forecast accuracy reduces the safety margin required to handle uncertainty, freeing up more tradable capacity. The FL model's superior adaptability during volatile periods implies stronger risk resistance for aggregators using the FL framework when risk events occur.

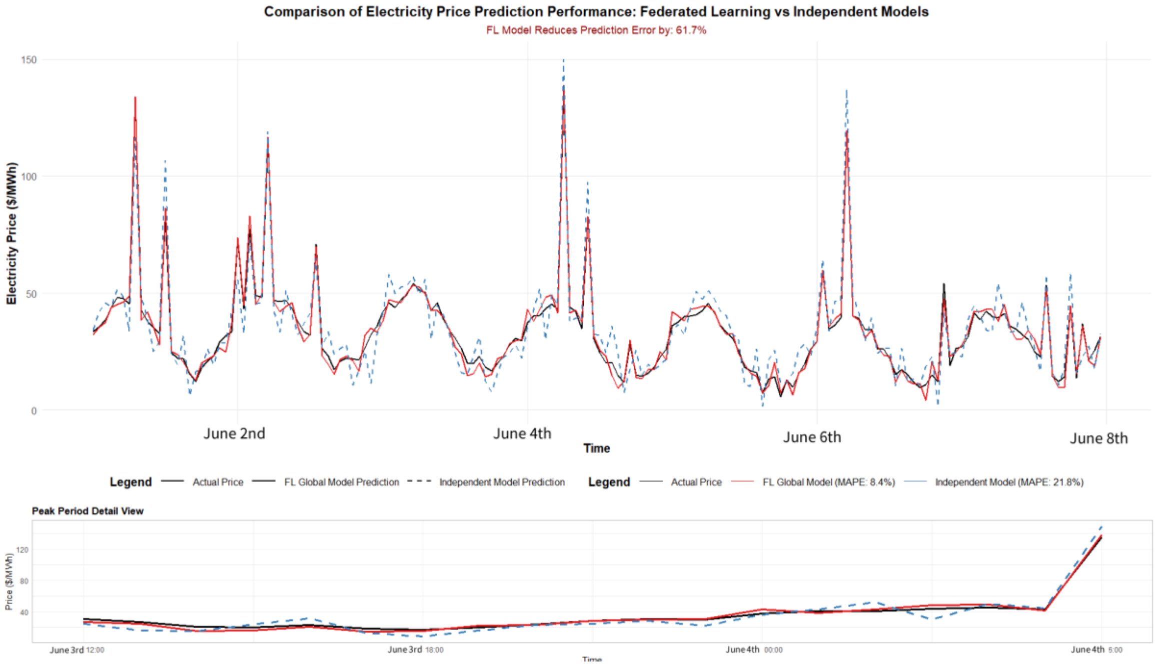


Figure 10. Comparison of Electricity Price Prediction Performance

Figure 10 compares the closeness of the FL global model's and independent models' forecasted price curves to the true price. As shown, the FL global model (red curve) tracks the true price (black curve) more closely than the independent model (blue curve), especially during periods of significant price fluctuation, highlighting the advantage of federated learning in enhancing prediction accuracy through knowledge sharing.

4.2. Case Study 2: Collaborative Multi-Agent Risk Control in Cross-Border Supply Chain Finance

4.2.1. Background and Problem Definition

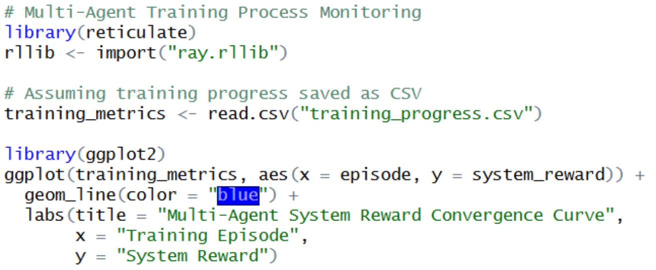
The global supply chain system faces challenges from multiple risk factors such as exchange rate fluctuations, logistics delays, and demand volatility. This case constructs a supply chain network comprising a core manufacturer, five key suppliers, and one financial institution, focusing on collaborative decision-making mechanisms under multi-risk environments [11].

The key research difficulty lies in how to minimize overall supply chain risk and maximize operational efficiency while protecting the commercial privacy of all participants.

4.2.2. Multi-Agent Reinforcement Learning Framework Design

This case employs a Multi-Agent Reinforcement Learning (MARL) approach, modeling each enterprise in the supply chain as an autonomous decision-making agent. Federated learning technology is responsible for training an assessment model of the supply chain's overall health status while protecting transaction data privacy [24].

The technical implementation comprises three main parts: using R's reticulate package to call Python's RLlib library for distributed training; utilizing R for policy evaluation, risk metric calculation, and network relationship visualization; using the output of the federated learning model as shared environmental information for each agent's decision-making.



```
# Multi-Agent Training Process Monitoring
library(reticulate)
rllib <- import("ray.rllib")

# Assuming training progress saved as CSV
training_metrics <- read.csv("training_progress.csv")

library(ggplot2)
ggplot(training_metrics, aes(x = episode, y = system_reward)) +
  geom_line(color = "blue") +
  labs(title = "Multi-Agent System Reward Convergence Curve",
       x = "Training Episode",
       y = "System Reward")
```

Figure 11. Code for Supply Chain Finance Simulation System

This code in Figure 11 reads the training progress data from the multi-agent reinforcement learning process and generates a line plot showing system reward versus training episodes. Execution produces a chart with Training Episode on the X-axis and System Reward on the Y-axis. An ideal convergence curve should show the system reward gradually increasing and eventually stabilizing as training progresses, indicating that the agents are learning effective collaborative strategies. This visualization is a crucial tool for assessing the success of the training process.

4.2.3. Simulation Implementation and Performance

The core logic of the simulation system is implemented through multi-agent training process monitoring, including training progress tracking and system reward convergence curve visualization.

A comprehensive evaluation index system was established: Joint Default Probability measures the likelihood of systemic default in the supply chain; Risk Transmission Intensity assesses the impact of a single node's risk on the system; Collaboration Benefit Index quantifies the improvement of cooperative decision-making compared to independent decision-making.

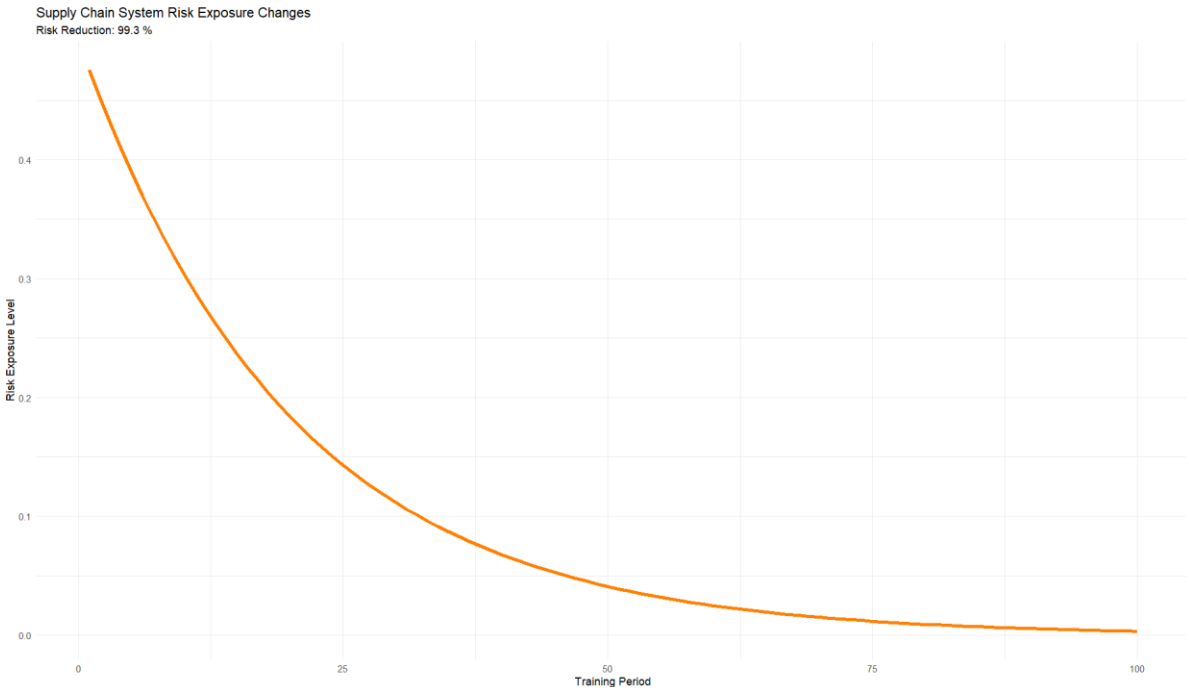


Figure 12. Risk exposure change chart of supply chain system

As shown in Figure 12, the changes in risk exposure levels over time for various nodes within the supply chain network after adopting the collaborative decision-making strategy. It can be observed that risk exposure generally decreases across nodes as training progresses, indicating that the collaborative risk control strategy is taking effect and the overall system risk level is reducing.

4.2.4. Result Verification and Management Implications

The experimental study yielded the following important conclusions:

In terms of risk identification, the federated learning-based collaborative risk assessment model could identify potential supply chain bottlenecks two to three weeks in advance, providing a valuable time window for risk prevention.

Risk control effects were significant, with the collaborative decision strategy reducing the probability of systemic cascading default by 25.3%, demonstrating good risk dispersion.

Operational benefits improved noticeably, with the overall supply chain profit level increasing by 15.8%, confirming the economic value of collaborative decision-making [11].

These findings validate the practical value of the FL-R framework in complex supply chain environments, providing managers with an effective tool for collaborative decision support.

The management implications of this improvement are: firstly, early risk identification allows managers to take preventive measures, avoiding risk accumulation and propagation; secondly, the reduction in default probability directly translates into lower capital costs, improving capital use efficiency; finally, the increase in profit level confirms the economic value of collaborative decision-making, providing empirical evidence for managers to promote cross-organizational collaboration.

4.3. Simulation Result Analysis and Discussion

In-depth analysis of the two case studies leads to the following key conclusions:

On the methodological level, the FL-R integrated framework successfully resolves the conflict between data privacy protection and collaborative efficiency enhancement in cross-market decision-making, providing a referable methodological guide for similar complex decision problems.

From a practical value perspective, the case study results show that the framework can generate significant economic benefits across different industry contexts, demonstrating broad application prospects.

In terms of theoretical innovation, this study elevates federated learning from a mere technical tool to a core component of management decision-making, enriching the content of intelligent decision theory systems.

The successful validation in these two cases lays a solid foundation for the application of the FL-R framework in wider fields and also points out directions for future development. The results demonstrate that the organic combination of federated learning and the R language can provide effective technical support and methodological guidance for complex cross-market decision problems.

5. Theoretical Innovation and Methodological Contribution

5.1. Privacy-Preserving Computation as an Endogenous Variable in Management Models

A primary theoretical innovation of this study is elevating privacy-preserving computation from a technical tool to an endogenous variable within management models [20]. Traditional cross-market decision research treats privacy protection as an external constraint, whereas this paper internalizes privacy protection as an organic component of the decision model through the FL-R framework.

The methodological significance of this paradigm shift is threefold: Firstly, it redefines the role of data privacy in decision sciences, transforming it from a limiting factor into a driver of innovation. Secondly, it provides a new path for knowledge sharing under the premise of protecting data sovereignty. Finally, it offers a theoretical framework and practical guidelines for building trustworthy AI systems.

Within the FL-R framework, privacy protection is no longer a cost for decision optimization but a catalyst for more efficient collaboration. Through secure multi-party computation and differential privacy techniques, the framework extracts collective wisdom while protecting individual privacy, achieving the theoretical breakthrough that "privacy protection does not imply knowledge loss" [12, 22, 27].

5.2. The Conduction Chain from Simulation Mechanism to Management Value

This study establishes a clear conduction chain: "Simulation Mechanism → Performance Metrics → Economic and Managerial Implications" [26]. Taking Case Study 1 as an example, the federated learning mechanism improves prediction accuracy (technical performance), optimizes bidding strategy (decision improvement), and ultimately increases risk-adjusted returns (economic value). Establishing this chain allows the economic significance of technical improvements to be quantified, providing a basis for managers to evaluate the return on technology investment.

In Case Study 2, the multi-agent reinforcement learning mechanism promotes collaborative decision-making (behavioral change), reduces systemic risk (risk improvement), and ultimately enhances overall supply chain profit (value creation). This conduction process reveals the internal logic of how technical mechanisms influence organizational performance by altering decision-making behavior [9].

6. Research Agenda and Future Development Path

Based on the framework and preliminary simulations of this study, a clear future research agenda is proposed:

Open-Source Tool Ecosystem Development: The core task is to develop and maintain the aforementioned AggregatorBiddingR software package, establishing it as a benchmark tool in the cross-market research field.

Theoretical Deepening: Game Theory and Incentives: In-depth research on incentive mechanism design in federated learning, integrating auction theory and contract theory into the framework to address the fundamental question of "who is willing to participate in federated learning."

Expanding Application Scenarios: Applying the framework to emerging fields such as carbon markets and data factor markets to test its generalizability.

"Explainable AI" Integration: Integrating explainability techniques like LIME and SHAP with FL models to enhance decision-makers' trust in "black-box" models.

7. Expected Theoretical, Methodological, and Practical Contributions

Theoretical Contribution: Constructs an interdisciplinary theoretical framework connecting privacy-preserving computation, decision sciences, and statistics.

Methodological Contribution: Provides a complete methodology and toolchain for the engineered integration of federated learning with the R language.

Practical Contribution: Offers feasible solutions for managers in industries like energy, finance, and supply chains to address decision-making challenges in the era of data silos.

8. Conclusion and Research Limitations

This paper systematically proposes the FL-R integrated modeling framework to address intelligent decision-making and risk management in cross-market bidding. Simulations based on two production-oriented case studies validate the framework's potential to enhance decision quality and control risk. The fundamental value of this research lies in its systemic thinking, closely integrating technical tools, management theory, and practical needs.

The study also has limitations: Firstly, although simulation data is based on real structures, there remains a gap compared to full-scale practical application. Secondly, the framework's computational complexity is relatively high, imposing certain demands on computing resources. Future work will focus on the implementation of open-source tools, testing with more empirical cases, and optimization of computational efficiency.

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