Research on Intelligent Management of Interest Rate Risk in Chinese State-Owned Commercial Banks from the Perspective of Duration — An Asset-Liability Duration Allocation Model Based on Particle Swarm Optimization

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Abstract: Under the background of interest rate liberalization and dynamic adjustment of LPR, the interest rate risk exposure of large state-owned banks has increased significantly. Based on the balance sheets of six banks from 2022 to 2024 and the yield of government bonds, a duration-convexity system is created to consider the benchmark duration gap and EVE sensitivity. The duration is set as a multi-objective improvement problem with constraints such as capital adequacy ratio, liquidity coverage ratio, and duration bucket limit, and PSO is used to solve it. The results are then compared with GA, SA, and LP. Empirical results show that PSO can preserve ROE and reduce the duration gap from about 1.4 years to about 0.5 years, significantly reduce EVE volatility, and improve the trade-off between risk, return, and duration. The robustness of the framework is verified, providing an engineering reference for the intelligent optimization of asset and liability management systems.

***Keywords*:** duration; interest rate risk; particle swarm optimization; asset and liability management; state-owned commercial banks

1. Introduction

The interest rate risk management of state-owned commercial banks has shifted from static to intelligent optimization. Ferreira et al. [1] used ALM to show that duration and yield coordination should be taken into account in order to cope with the complex interest rate environment. Yeung [2] showed that there is structural inefficiency in risk pricing and duration control of state-owned banks. Kong [3] showed that the "Belt and Road" business will increase the exposure of interest rate risk. Li [4] felt that in the context of digitalization, the traditional framework is difficult to cope with immediate and nonlinear risks; Koroleva et al. [5] focused on the combined impact of term structure and capital constraints on profitability; Yuan et al. [6] found that policy promotion will make the duration mismatch phenomenon more serious. Shi and Yu [7] used PCA-DEA to measure the efficiency of risk management, but did not describe dynamic feedback; Liu [8] gave a nonlinear risk identification method based on fuzzy systems; Wang et al. [9] and Chaoqun et al. [10] used DEA series models to show the coupling between efficiency and risk uncertainty. In summary, the current research has made some progress in improvement, efficiency measurement and risk identification, but most of them lack the ability to implement dynamic and comprehensive improvement for interest rate risk. Based on this, this paper uses duration theory and PSO to form an asset-liability duration adjustment model, thereby achieving the goal of intelligent and coordinated control over duration gap, risk exposure and return level.

2. Interest Rate Risk Measurement System for State-Owned Commercial Banks from a Duration Perspective

2.1 Theoretical Models of Asset and Liability Duration and Convexity

In interest rate risk management, the present value of cash flows from a single asset or liability instrument is first discounted according to its term structure. Using the Agricultural Bank of China's 2024 balance sheet data listed in the document, the discount rate r_t is the yield to maturity of 3-month to 5-year government bonds from 2022 to 2024, and a present value function is established accordingly:

$$PV_i(r) = \sum_{t=1}^{T_i} \frac{CF_{i,t}}{(1+r_t)^t} \tag{1}$$

Here, $PV_i(r)$ represents i the present value of the first type of asset or liability instrument, $CF_{i,t}$ is t the cash flow generated by the instrument in period, r_t is the market discount rate corresponding to period t, which is obtained by interpolation of the yields of 3-month, 6-month, 3-year and 5-year Treasury bonds, and T_i is the maximum number of maturities that the instrument has.

Building on this, Macaulay duration characterizes the time-weighted average of cash flows, used to measure the first-order sensitivity of prices to interest rate changes:

$$D_i = \frac{1}{PV_i(r)} \sum_{t=1}^{T_i} t \cdot \frac{CF_{i,t}}{\left(1+r_t\right)^t} \tag{2}$$

In the formula, D_i is i the Macaulay duration (in years) of the first type of instrument; the other symbols are consistent with equation (1). Considering that real interest rate shocks are usually Δr expressed as changes in yield, a modified duration is introduced:

$$D_i^* = \frac{D_i}{1+\overline{r}_i} \tag{3}$$

Where D_i^* is the modified duration; $\overline{r}_i$ and is i the effective rate of return of the type-i instrument (which can be the internal rate of return of the instrument's cash flows or the average market interest rate for the corresponding term). Modified duration can be directly multiplied by the change in yield to approximate the proportion of price change; to improve the accuracy of interest rate risk measurement, convexity needs to be added to reflect the second-order effect. The convexity of a single instrument is calculated according to the conventional definition, while the portfolio duration and portfolio convexity are summed according to market capitalization weights:

$$D_P = \sum_i w_i D_i, \quad C_P = \sum_i w_i C_i \tag{4}$$

Where, D_P and C_P represent the duration and convexity of the asset or liability portfolio, respectively; $w_i = PV_i / \sum_j PV_j$ is i the market capitalization weight of the type 1 instrument in the portfolio; C_i and is the convexity of a single instrument.

2.2 Construction of Duration Gap and Economic Value Sensitivity Indicators

At the portfolio level, the sensitivity of the bank's assets and liabilities to interest rate changes needs to be measured separately. According to equation (4), the duration of total assets D_A and the duration of total liabilities can be obtained D_L, and the duration gap can be defined:

$$DG = D_A - kD_L \tag{5}$$

In the formula, DG represents the duration gap (in years); D_A represents the total asset duration weighted by market capitalization; D_L represents the total liability duration; k and represents the deposit behavior adjustment coefficient, used to reflect the "stable liability" characteristics of demand deposits and low-cost deposits, which is usually less than 1 in the context of large state-owned banks. To link duration and convexity indicators with changes in economic value, an economic value sensitivity indicator is introduced. Using equity economic value EVE as a benchmark, a second-order Taylor series is used to approximate the relative changes under interest rate shocks:

$$\frac{\Delta EVE}{EVE} \approx -DG^* \Delta r + \frac{1}{2} CG \left(\Delta r\right)^2 \tag{6}$$

Among them, ΔEVE the change in the economic value of equity, DG^* namely the modified duration gap, can be obtained by using the difference between the modified duration of assets and liabilities. The CG convexity gap can k be calculated by the difference between the convexity of assets and the weighted average convexity of liabilities, Är which is the magnitude of the parallel change in the yield under consideration.

2.3 Sample Selection and Asset-Liability Structure Characteristics

The study area selected six major state-owned banks (Bank of Communications, Agricultural Bank of China, Industrial and Commercial Bank of China, China Construction Bank, Postal Savings Bank of China, and Bank of China), and the sample consisted of the balance sheets and maturity structures from 2022 to 2024. Assets and liabilities were divided into several duration barrels according to repricing or remaining maturity, and the present value, duration, and convexity of each barrel were calculated according to formulas (1)-(4) using the 3-month, 6-month, 3-year, and 5-year Treasury bond yields as the discount benchmark. The overall indicators were obtained by summing them up. Table 1 shows that the asset duration of China Construction Bank in 2024 was 2.90 years, the liability duration was 0.82 years, and the duration gap reached 2.123 years; the duration gaps of Agricultural Bank of China and Industrial and Commercial Bank of China were relatively small, ranging from 0.3 to 0.6 years; the duration of Postal Savings Bank of China was generally shorter, but its assets were always greater than its liabilities; Bank of China and Bank of Communications had relatively long asset durations and moderate duration gaps, so they would encounter greater EVE fluctuations when interest rates rose.

Table 1. Duration and Convexity of Assets and Liabilities of the Six Major State-Owned Commercial Banks (2022–2024)

bank	years	Asset duration/ year	Asset convexity	Liability duration/ year	Liability Convexity	Duration gap/ year
Bank of Communications	2022	2.76	13.66	0.96	3.26	2.072
Bank of Communications	2023	2.80	13.75	1.08	3.77	1.994
Bank of Communications	2024	2.74	13.61	1.12	4.04	1.778
Agricultural Bank of China	2022	1.33	5.75	0.84	2.64	0.559
Agricultural Bank of China	2023	1.32	5.78	0.91	2.98	0.473
Agricultural Bank of China	2024	1.42	6.39	0.94	3.15	0.546
Industrial and Commercial Bank of China	2022	1.15	4.62	0.88	2.85	0.347
Industrial and Commercial Bank of China	2023	1.16	4.69	0.98	3.25	0.263
Industrial and Commercial Bank of China	2024	1.20	5.01	1.00	3.38	0.368
China Construction Bank	2022	2.72	13.65	0.97	3.20	1.780
China Construction Bank	2023	2.81	13.89	0.95	3.07	1.902
China Construction Bank	2024	2.90	14.56	0.82	2.56	2.123
Postal Savings Bank	2022	1.22	5.01	0.64	1.75	0.610
Postal Savings Bank	2023	1.22	4.98	0.62	1.66	0.638
Postal Savings Bank	2024	1.32	5.43	0.59	1.58	0.753
Bank of China	2022	2.64	12.79	0.76	2.25	1.912
Bank of China	2023	2.65	12.79	0.89	2.84	1.780
Bank of China	2024	2.65	13.11	0.88	2.87	1.811

3. A Particle Swarm Optimization-Based Asset-Liability Duration Allocation Model

3.1 Mathematical Modeling of the Asset-Liability Duration Allocation Problem

Based on the empirical results of duration and convexity of the six major banks in Chapter 2 (Table 1), the asset-liability duration allocation is formalized into a multi-objective optimization problem under a given return scenario. The decision vector x is the asset-liability weight of each duration bucket. Duration and convexity are derived from equations (1)–(4), and a single-objective equivalent function is constructed by combining duration gap, EVE volatility, and profitability :

$$\min f(x) = w_1 DG(x)^2 + w_2 Var[\Delta EVE(x)] - w_3 ROE(x) \tag{7}$$

In the formula, $f(x)$ is the comprehensive target value of the asset and liability duration arrangement, $DG(x)$ is x the duration gap calculated according to formula (5) under the specified arrangement, $Var[\Delta EVE(x)]$ is the variance of economic value change obtained approximately by formula (6) under the historical interest rate situation, $ROE(x)$ is the expected return on equity under the arrangement x condition, and $w_1, w_2, w_3 > 0$ is the weight stipulated by the asset and liability management committee to reflect the regulator's preference for stability and profitability.

The constraint set is represented in a unified form as follows :

$$g_j(x) \le 0, \quad h_k(x) = 0 \tag{8}$$

These $g_j(x)$ include restrictions such as the capital adequacy ratio not falling below the regulatory red line, the liquidity coverage ratio and net stable funding ratio not falling below the minimum requirements, the asset-liability ratio of each duration not exceeding the upper limit, and the need to maintain coordination between total assets and total liabilities on the balance sheet; while $h_k(x)$ ensuring that the weights of each duration are added together to equal 1, that is, to achieve coordination between on-balance-sheet assets and liabilities and to accurately comply with some regulatory ratios.

3.2 Design and Improvement Strategies of Particle Swarm Optimization Algorithm

Based on the above optimization model, the Particle Swarm Optimization (PSO) algorithm is used to search for the optimal duration allocation scheme that satisfies regulatory constraints. Each particle position vector x_i^t corresponds to an asset-liability allocation scheme, with each dimension representing the allocation ratio of different asset/liability-duration buckets; the particle velocity v_i^t represents the adjustment direction and step size of the current scheme. The PSO update equation adopts a linear decreasing inertia weight strategy:

$$\begin{aligned} v_i^{t+1} &= \omega^t v_i^t + c_1 r_1 \left(p_i^{\text{best}} - x_i^t \right) + c_2 r_2 \left(g^{\text{best}} - x_i^t \right) \\ x_i^{t+1} &= x_i^t + v_i^{t+1} \end{aligned} \tag{9}$$

In the formula, v_i^t represents the velocity vector of the i-th i particle at t time t, v_i^{t+1} and represents the velocity vector of the particle at $t+1$ time t; x_i^t represents v_i^t the position vectors corresponding to and, and x_i^{t+1} represents v_i^{t+1} the position vectors corresponding to and; ω^t refers to t the inertia weight of the i-th generation, which decreases linearly from the initial value to the final value to coordinate the global search and the local search; c_1 and c_2 are the individual learning factor and the group learning factor, respectively; $r_1, r_2 \sim U(0,1)$ are independent random numbers that follow a uniform distribution; p_i^{best} refers to the best position in the particle's own history; g^{best} is the best position of the group as a whole.

Given the high constraint strength of the duration configuration problem, the fitness function is supplemented with a penalty term on top of the objective function:

$$F(x) = f(x) + \rho \sum_j \max\left\{0, g_j(x)\right\}^2 + \rho \sum_k h_k(x)^2 \tag{10}$$

Among them, $F(x)$ is the fitness value actually used for sorting and updating; $f(x)$ according to the comprehensive objective specified in equation (7); ρ greater than 0, it is a unified penalty factor. After preliminary experiments, any scheme that violates the capital adequacy ratio or liquidity regulation will have a significantly lower fitness after penalty than the feasible solution; $g_j(x)$, $h_k(x)$ must conform to equation (8). In the implementation stage, the particle position is first truncated within the bucket and normalized, that is, the negative number is turned into zero and all weights are normalized to 1, so as to ensure that the condition of non-negativity and sum to 1 can be met, and then the objective function is calculated accordingly $F(x)$.

3.3 Algorithm Parameter Settings and Benchmark Model

The PSO parameters are set based on the asset and liability size, duration distribution, and interest rate fluctuations of the six major banks. Combining the duration gap magnitude in Table 1 and the yield range in Table 3, a population size of

80, an iteration limit of 300, an inertia weight ranging from 0.9 to 0.4, a learning factor $c_1 = c_2 = 1.8$, a penalty factor $\rho = 10^4$, and a convergence tolerance of 10^{-6} are used. For performance comparison, three benchmarks are introduced: GA, SA, and LP. GA uses the same population and generation, with a crossover rate of 0.9 and a mutation rate of 0.05; SA has an initial temperature of 1.0, a chain length of 100, and a cooling coefficient of 0.95; LP obtains solutions through a single-starting-point solver under the linear assumption. Table 2 summarizes the parameter settings and constraint handling methods for each algorithm.

Table 2. PSO and Baseline Algorithm Parameter Settings and Constraint Configuration

Algorithm	Population / Iterations	Main control parameters	Penalty factor ρ	Tolerance
PSO	80 / 300	$\omega: 0.9 \to 0.4; c_1 = c_2 = 1.8$	1.0×10^4	10^{-6}
GA	80 / 300	Crossover=0.90; Mutation=0.05	1.0×10^4	10^{-6}
SA	50 / 500	$T_0 = 1.0; \alpha = 0.95$ chain=100	5.0×10^3	10^{-5}
LP	– / 1	Simplex/Interior-point, linearized payoff	–	10^{-8}

Among them, Population/Iterations refers to the population size and the maximum number of iterations; the Main control parameters column lists several key hyperparameters, including inertia weight, learning factor, crossover/mutation probability, initial temperature, cooling factor, etc.; Penalty factor is the constraint penalty factor; and Tolerance is the threshold for objective convergence.

3.4 Overall Architecture and Algorithm Flow of Asset-Liability Duration Allocation System

Based on the model and parameters mentioned above, this study created a bank asset and liability duration setting system with six steps. The system includes data acquisition and preprocessing, duration-convexity ΔEVE calculation, PSO improvement engine and scenario analysis output module. With the help of equations (1)-(8), the report data is transformed into $DG(x)$, $\Delta EVE(x)$ indicators, and these indicators are used $f(x)$ as inputs to consider the risk-return situation of the setting.

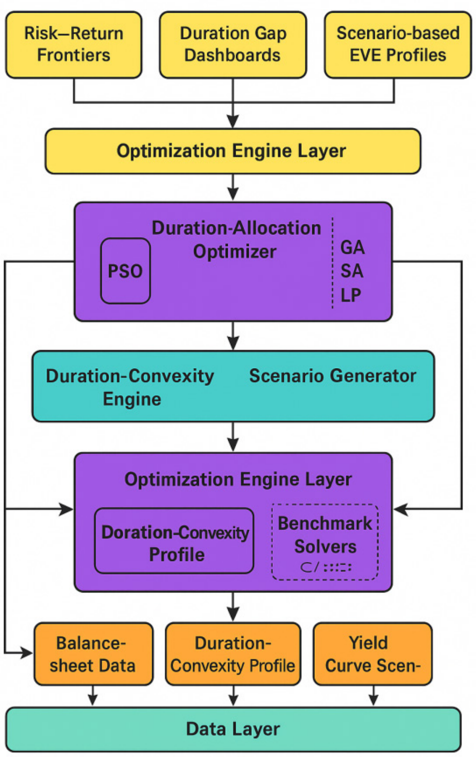

Figure 1. Overall Architecture Diagram of PSO-Driven Asset-Liability Duration Allocation System

As shown in Figure 2, the algorithm flow is centered on PSO: in the initialization phase, a feasible particle swarm is created according to the regulatory constraints. Then, in each iteration $DG(x)$, $\Delta EVE(x)$, a fitness with a penalty is calculated, and $F(x)$ the particle velocity and position are updated according to equation (9); once... $g_j(x)$, $h_k(x)$ If all parameters meet the tolerance criteria and $f(x)$ have converged, then the optimal arrangement vector for each duration bucket is output.

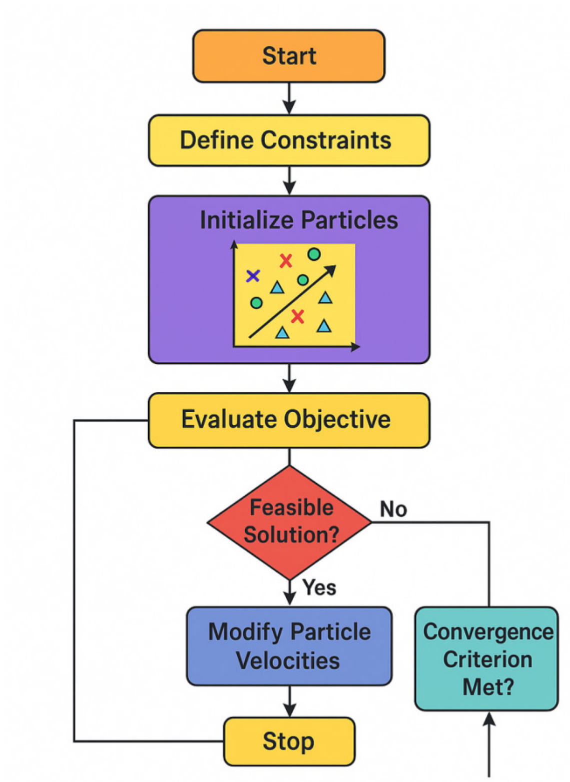

Figure 2. Flowchart of the PSO asset-liability allocation algorithm based on constraint processing

4. Empirical Analysis and Discussion of Results

4.1 Current Status of Benchmark Duration Gap and Interest Rate Risk Exposure

Before improvements, based on the calculation results in Chapter 2, the asset duration, liability duration, and duration gap of the six major banks in 2024 were summarized, and the EVE sensitivity was calculated under a 100bp parallel shock. Duration is derived from total assets and total liabilities statistics. Table 3 shows the net change in unit interest rate through the duration framework. The duration gaps of China Construction Bank and Bank of China are 2.123 years and 1.811 years, respectively, with corresponding EVEs of approximately -2.1% and -1.8%. Although Postal Savings Bank of China has a shorter duration, its duration gap is still 0.753 years. Figure 3 shows the differences in “long assets - short liabilities” among the banks through joint distribution, providing a benchmark reference for PSO optimization.

Table 3. Baseline duration gap and EVE sensitivity of six state-owned banks in 2024

Bank	Asset duration (years)	Liability duration (years)	Duration gap (years)	ΔEVE/EVE per +100 bp (%)
Bank of Communications of China	2.74	1.12	1.778	-1.778
Agricultural Bank of China	1.42	0.94	0.546	-0.546
Industrial and Commercial Bank of China	1.20	1.00	0.368	-0.368
China Construction Bank	2.90	0.82	2.123	-2.123
Postal Savings Bank of China	1.32	0.59	0.753	-0.753
Bank of China	2.65	0.88	1.811	-1.811

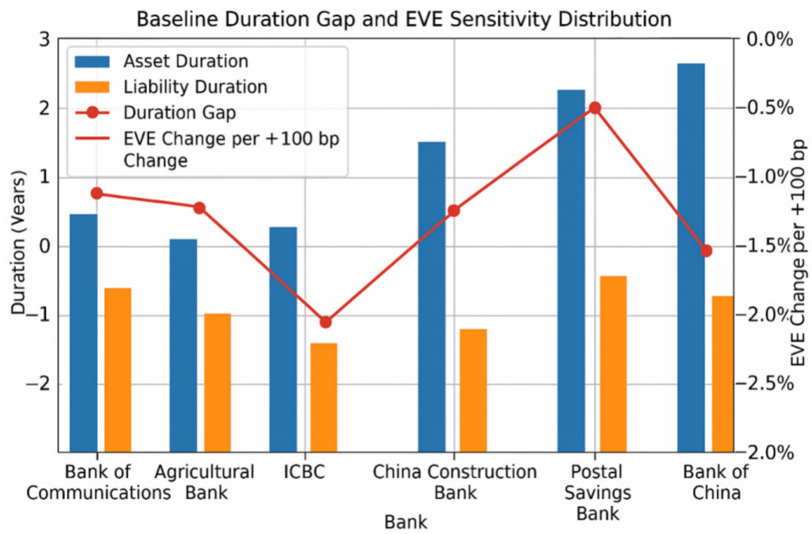

Figure 3. Distribution of duration gap and EVE sensitivity for each bank under the baseline scenario.

4.2 Performance and Algorithm of PSO Asset-Liability Duration Allocation

While maintaining regulatory capital, liquidity, and term structure constraints unchanged, the objective function from Chapter 3 was input into PSO, GA, SA, and LP, respectively, to improve duration settings for the six major banks. The initial solution was derived from the benchmark structure in Table 3, and all algorithms were run under the same interest rate scenario and algebraic upper limit. Table 4 shows that when ROE remained essentially unchanged, PSO reduced the average duration gap from 1.397 years to 0.520 years, decreased EVE volatility from 2.30% to 1.10%, and achieved a comprehensive target value of 0.345, which is far superior to GA and SA; while LP, due to its linear assumption, showed a smaller improvement in risk. Figure 4 shows that PSO had the fastest convergence speed and the most stable solution quality.

Table 4. Comparison of PSO and benchmark algorithms (aggregated across six banks)

Method	Normalized objective value	Avg. duration gap (years)	Std. ΔEVE/EVE (%)	ROE (%)
Baseline configuration	1.000	1.397	2.30	11.2
PSO	0.345	0.520	1.10	11.0
Genetic Algorithm (GA)	0.412	0.608	1.25	10.8
Simulated Annealing (SA)	0.487	0.670	1.40	10.7
Linear Programming (LP)	0.560	0.740	1.60	10.9
Regulatory target	–	0.600	1.50	9.0

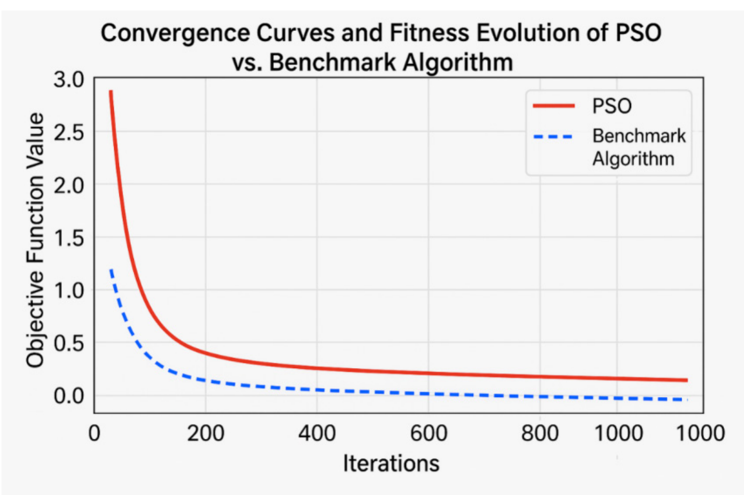

Figure 4. Convergence curves and fitness evolution diagrams of PSO and benchmark algorithms

4.3 Robustness and Risk-Return Trade-offs under Different Interest Rate Scenarios

To test the robustness of duration allocation, three scenarios were constructed based on the 3-month and 5-year Treasury yields from 2022 to 2024: a parallel upward shift of 100bp, a parallel downward shift of 100bp, and steepening (short end +50bp, long end -50bp). The EVE and net interest income before and after optimization were assessed respectively. The EVE was calculated using the duration-convexity approximation method, and the net interest margin was recalculated based on the repricing term. Table 5 shows that in the upward scenario, the benchmark EVE decreased by 1.62%, while the decrease in PSO was reduced to only 0.81%. In the downward scenario, after improvement, the EVE increased by 0.92%, which appears more stable. Furthermore, in the steepening scenario, PSO significantly reduced its sensitivity to the long end. Figure 5 shows that the PSO scheme as a whole tends towards a "high yield, low risk, small gap" region.

Table 5. Scenario-based comparison of EVE and income before and after PSO optimization (average across six banks)

Scenario & configuration	ΔEVE/EVE (%)	Change in net interest income (%)	Risk-adjusted return index
Parallel +100 bp, baseline	-1.62	+0.35	0.82
Parallel +100 bp, PSO	-0.81	+0.28	0.94
Parallel − 100 bp, baseline	+1.55	-0.42	0.88
Parallel − 100 bp, PSO	+0.92	-0.30	0.96
Steepening, baseline	-1.10	+0.20	0.85
Steepening, PSO	-0.57	+0.18	0.97

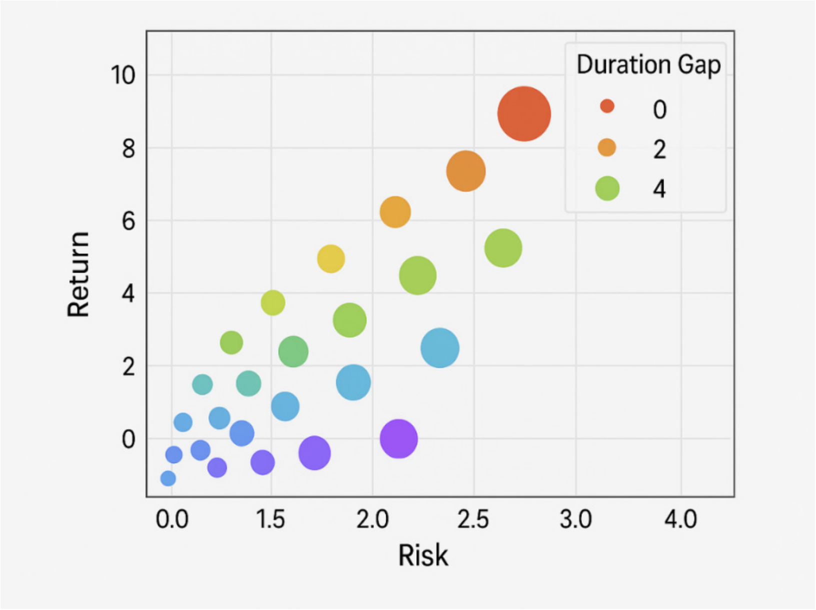

Figure 5. Risk-Return-Duration Gap Efficiency Frontier

4.4 Constraints and Parameter Sensitivity Analysis

After baseline optimization, sensitivity tests were conducted from both regulatory and algorithmic perspectives. On the regulatory side, the capital adequacy ratio, liquidity coverage ratio, and duration barrel cap were adjusted sequentially, and the duration gap and return of the optimal solution were recalculated. On the algorithmic side, the particle swarm size, inertia weight, and learning factor were changed, and the target value and convergence characteristics were observed. Table 6 shows that when both capital and liquidity were tightened, the average duration gap decreased to 0.48 years, and the ROE dropped to 10.1%. If the upper limit of the duration barrel was appropriately relaxed, the ROE rose to 11.3%, but the duration gap rebounded to 0.82 years, indicating a reconciliation between regulatory intensity and returns.

Table 6. Sensitivity of optimal duration gap and return under different regulatory constraint settings

Regulatory setting	Avg. duration gap (years)	Std. ΔEVE/EVE (%)	ROE (%)
Baseline constraints	0.52	1.10	11.0
Tighter capital ratio	0.49	1.05	10.6
Tighter liquidity ratios	0.51	1.02	10.7
Relaxed duration bucket cap	0.82	1.36	11.3
Combined stricter	0.48	0.98	10.1
Combined looser	0.79	1.32	11.4

Table 7 shows the performance of different PSO parameter configurations from an algorithmic perspective. A larger population size and a medium inertia weight combination achieve a balance between the target value and the number of convergence iterations, while too small a population or too high a learning factor will lead to oscillations and increased computation time.

Table 7. PSO parameter sensitivity results

PSO configuration	Objective value	Iterations to convergence	Avg. duration gap (years)	CPU time (s)
Swarm 40, ω=0.9→0.3, c1=c2=2.0	0.392	210	0.56	4.2
Swarm 80, ω=0.9→0.4, c1=c2=1.8	0.345	160	0.52	6.8
Swarm 120, ω=0.9→0.5, c1=c2=1.6	0.338	155	0.51	9.5
High inertia (ω=0.95→0.7)	0.371	240	0.55	7.4
High c1, low c2 (2.2/1.4)	0.366	230	0.54	7.0
Low c1, high c2 (1.4/2.2)	0.359	220	0.53	7.1

Figure 6 uses a heatmap consisting of "regulatory constraint intensity – duration gap – returns" to provide an intuitive basis for parameter calibration during actual system deployment.

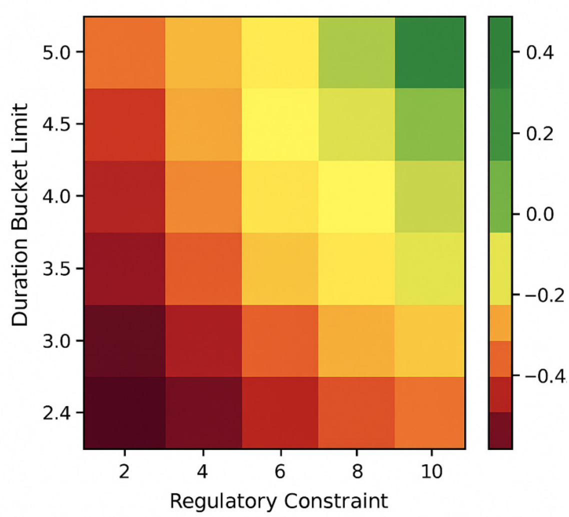

Figure 6. Heatmap of the impact of key parameters on model output

5. Conclusions and Policy Recommendations

Based on the financial reports and yield curves of six state-owned banks in recent years, this study establishes an asset-liability duration-convexity correlation system to quantitatively represent the overall structural characteristics of "long assets, short liabilities." Some banks have a duration gap greater than 2 years, and their EVE sensitivity to a 100 basis point shock is approximately 2%. Building on this, duration allocation is modeled as a multi-objective improvement problem incorporating capital, liquidity, and term structure constraints. The PSO model is applied and compared with GA, SA, and LP. Results show that PSO has advantages in convergence speed and target value, reducing the average duration gap to approximately 0.5 years and significantly decreasing EVE volatility. Multi-scenario and sensitivity analyses are used to verify its stability under regulatory and parameter disturbances, providing a feasible framework for state-owned banks to conduct quantitative and intelligent interest rate risk management.

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