

## Research Article

# A GD-PSO Algorithm for Smart Transportation Supply Chain ABS Portfolio Optimization

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Financial technology and smart transportation is key cross-field of transportation in the future. The demand for smart transportation investment is constantly released. As typical and efficient financial products, asset-backed securities (ABS) can greatly improve the turnover efficiency of funds between upstream suppliers and downstream buyers in the field of smart transportation and also help participants of the supply chain to maintain healthier financial situations. However, one of the most common problems of ABS is portfolio allocation, which needs portfolio optimization based on massive assets with multiple objectives and constraints. Especially, in the field of smart transportation, sources of underlying assets can always be complex, which may involve a variety of subdivision industries and regions. At the same time, due to the relationships between upstream and downstream entities in the supply chain, correlations among assets can be strong. So, during the optimization of smart transportation ABS portfolio allocation, it is necessary to identify and deal with those problems. Different from forward selection or linear optimization, which could have low efficiency for complicated problems with large sample size and multiple objectives, new methods and algorithms for NP-hard problems would be necessary to be investigated. In this article, a penalty function based on graph density (GD) was introduced to the particle swarm optimization algorithm (PSO), and a GD-PSO algorithm was proposed. Experiments also showed that the GD-PSO algorithm solved the problem of portfolio optimization in smart transportation supply chain ABS effectively.

## 1. Introduction

Smart transportation has been developed rapidly as a new field in China. The field of smart transportation involves a wide range of areas, including dozens of industries, such as transportation, construction, equipment manufacturing, information technology, leasing, and finance. Project operation often involves the flow of a huge volume of materials and funds between upstream and downstream entities. Supply chain financing is naturally a necessary mode of financial services in smart transportation. The application of asset-backed securities (ABSs) in this field is a good example with an innovative form, that is, based on a much better credit status of a downstream buyers entity or group, the accounts receivable held by the upstream suppliers can bring

static expected cash flow in the future. By issuing ABS with those liabilities as underlying assets on the capital market, funds can be raised with lower interests and higher efficiency. Compared with traditional financing methods, another important advantage of supply chain ABS is that it usually has a credit guarantee from the core enterprises member with higher credit rating, which can greatly improve the ABS rating and control financial risks on the market.

Du and Zhou [1] studied the feasibility of supply chain ABS in China and got positive results about its application. Liang [2] also discussed the advantages of supply chain ABS of accounts receivable for small- and medium-sized enterprises in the transportation industry. Yang [3] found that it would be active and useful to employ financial leasing mode

for smart transportation projects, especially in the way of ABS. With rapid developments of smart transportation, the amount of ABS issued in this field was also increasing year by year (Figure 1).

However, the underlying assets of ABS usually have the following characteristics: small amount, high variation, and short term. After securitization, it is very likely to produce problems of mismatch between assets and the design of ABS, which can lead to short coverage of asset cash flow to securities payment, and the repayment risk of ABS can increase accordingly. Therefore, more and more ABS on the market are running with a circular purchase structure. The so-called circular purchase means that cash flow generated by underlying assets within a specific period of time is not fully used to pay to the investors. Instead, it is used to purchase new qualified underlying assets continuously.

At the same time, circular purchase in ABS is not a simple repeat purchase of underlying assets with funds in trust accounts accumulated by cash inflow of underlying assets purchased earlier, but a complicated transaction decision with multiple objects and constraints such as maximized amount, optimized structure, and controllable risks. For some smart transportation supply chain ABS, these decisions should be made every day. So, selecting assets from hundreds, thousands, or even millions of loans meeting those requirements has been a difficult problem because the amount of computation is huge and the objectives and constraints are complex and can contradict each other on some level.

What is more, in the field of smart transportation supply chain ABS, there are more difficulties raised from the relationships between upstream and downstream companies, entities with parallel positions, or other obligatory relationships in the supply chain. This means that the allocation of portfolio and control of granularity of assets will affect the risk exposures of portfolios directly.

As a result, in practice, only for ABS with a small number of assets, portfolios allocation could be made by setting simple screening rules to determine whether or not to select a single asset or sorting assets based on some dimensions and then dividing the whole parent pool. Although this method was useful for ABS with a few underlying assets, it would never meet all the requirements at the same time in complex situations, such as the total balance, amount of weighted average life, and diversification with a parent assets pool with a large number of samples. Another important drawback of this approach was the inability to optimize. For example, the size of the circular purchase package could be too small, the balance left in the trust special account could be too high, which would lead to excessive costs of deposition; or the final asset package might meet the requirements of weighted average age, maximum scale, and so on., but it did not reach the optimal diversification or reduce the risk of the portfolio to a level as low as it could be.

To solve the problems in portfolio selection and optimization in ABS with a circular purchase structure, researchers have conducted relatively few studies; a few studies about the ABS market in China are expected. Lei [3, 4] revealed that a circular purchase could face difficulties with

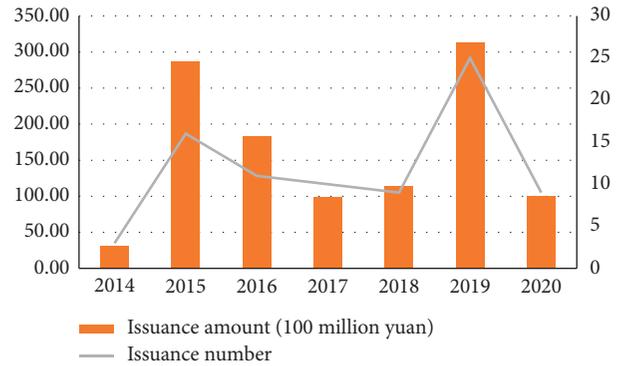


FIGURE 1: Supply chain ABS issuance (100 million yuan).

accounting. With more details, Lu Binbin [5, 6] discussed the motivation for circular purchase and potential problems during product design. At the same time, risks unique to the structure of circular purchase were analyzed, and the shortage of underlying assets supply as a primary problem was pointed out. Lu [7, 8] also provided suggestions on operations of circular purchase in ABS portfolio construction, focusing on building up an automatic and intelligent system; otherwise, the high-frequency circular purchase can not be realized.

About the optimization methods, with the introduction of genetic algorithms, tabu search, simulated annealing, neural networks, and a series of traditional or intelligent optimization algorithms, the efficiency and results of portfolio optimization had been improved greatly. For example, Chang et al. [9] developed heuristic algorithms based on genetic algorithms, tabu search, and simulated annealing and investigated the characteristics of the efficient frontiers. It was shown that problems could be harder with particular constraints but still could be solved even with discontinuous efficient frontiers. Fernández and Gómez [10] applied a neural network algorithm to the problem of portfolio selection with a given number of assets and limited capital amount. The algorithm performed well and showed some advantages compared with previous methods. The particle swarm optimization (PSO) algorithm was built up based on the principle of how bird swarms search in space [11] and could solve nonlinear optimization problems efficiently with fast convergence speed, especially in a high-dimensional space. Cura applied it to the optimization of venture capital portfolio and got positive results in efficiency and effectiveness [12]. However, although the PSO algorithm occupied some advantages for problems with a huge number of assets, it did not consider the relationships between dimensions, which could always be one of the most important facts for portfolio optimization of smart transportation supply chain ABS.

Considering those problems during the optimization of portfolios in smart transportation supply chain ABS, graph density (GD) was introduced to describe the correlations between assets and the objective function was rewritten by adding a penalty term based upon GD. Then, an algorithm based on PSO and Graph GD (GD-PSO) was proposed in

this article. The experiments showed that the NP-hard problem with large sample size in smart transportation supply chain ABS portfolio optimization had been solved efficiently with GD-PSO. Compared with simple PSO and forward selection algorithm, GD-PSO showed obvious advantages in convergence and efficiency. Thus, with the algorithm of GD-PSO, the multiple requirements, including high frequency, volume optimization, cost management, and risk control, in portfolio allocation for smart transportation supply chain ABS had been met, and better results were achieved.

In the following components of this article, the problem description, mathematical formulation, and algorithm design are provided in Section 2. In Section 3, a computational example and the comparison between GD-PSO and pure PSO method are discussed. Conclusions are shown in Section 4.

## 2. Model Design

*2.1. Problem Description and Mathematical Model.* Based on the analysis of smart transportation ABS issued in China, considering the characteristics of product form, issuing mechanism, debtor and creditor selection, cash flow collection and distribution, supplier subsidy, and so on, constraints and objects should be considered in the issuance and circular purchase of smart transportation supply chain ABS as discussed in this article.

### 2.1.1. Constraints in Smart Transportation Supply Chain ABS Portfolio Allocation

(1) *Total Balance of Underlying Assets.* For the issuance or circular purchase of supply chain ABS, there are often requirements of upper limits about total assets in the balance sheet of the portfolio. For ABS, which adopts a storage shelf mechanism as early as the time of applying for issuance, there has been a clear agreement on the total and circular purchase amount of underlying assets, meaning that the issued or circularly purchased assets can never exceed the upper limit of the agreed total or residual amount. Especially for products with circular purchase mechanism, funds for circular purchase often come from the balance of a special account held by a trust institution and usually get limits to keep the account still having funds after circular purchases, with a certain coverage rate to unpaid principal and interests of the ABS. An inequality for constraints in total amount was formed as follows:

$$\sum_{i=1}^{i=k} \text{BAL}_i \leq \text{TBAL}_{\text{ul}}, \quad (1)$$

where  $k$  was the number of accounts receivable included in the selected portfolio,  $\text{BAL}_i$  was the balance of a single asset  $i$  selected into the portfolio.  $\text{TBAL}_{\text{ul}}$  was the upper limit of assets to be issued or circularly purchased due to the issuance declaration, trust account balance, and so on..

(2) *Age of Accounts Payable.* For entities located at the downstream stage of a supply chain, liabilities selected into the ABS portfolios should be repaid before the payment day of the ABS. Therefore, to extend the account period successfully, the number of days from issuance or circular purchase to the next payment day of ABS should be longer than the ages of liabilities involved in the ABS as underlying assets. Let  $\text{TERM}_{\text{ul}}$  be the number of days to the payment day of ABS and  $\text{TERM}_i$  the age of assets  $i$  in the portfolio; then, the constraint about the age of accounts payable should be as follows:

$$\max(\text{TERM}_i, 1 \leq i \leq k) \leq \text{TERM}_{\text{ul}}. \quad (2)$$

At the same time, considering the cost of financing, the weighted average life was required not to exceed a certain value. Since there were generally no interest costs in the accounts payable itself, only age distribution needed to be discussed. Let the amount of weighted life of assets included in the portfolio be  $\text{WTERM}$ , the average interests rate of capital for the debtor during the period of ABS ( $T$ ) be  $R$ , and, with the considering of excess subsidy to suppliers, the financing cost of ABS be  $\text{RABS}$ , while it was issued; then, financing costs savings of downstream buyers should be  $R * \text{Portfolio size} * (T - \text{WTERM}) - \text{RABS} * (\text{Portfolio size}) * T$ . If those savings were required to be greater than 0, or a certain value, while other variables in the formula were determined,  $\text{WTERM}$  would have an upper limit. That is to say, when the amount and costs of financing were fixed, only if the amount of weighted average life of those assets in the portfolio was below a certain threshold, aims of financing costs saving and liquidity pressure relieving could be achieved. The constraint condition in amount of weighted average life was shown in the following:

$$\frac{\sum_i^k \text{TERM}_i \times \text{BAL}_i}{\sum_i^k \text{BAL}_i} \leq \text{WTERM}_{\text{ul}}. \quad (3)$$

(3) *Asset Diversification.* For supply chain ABS, there was usually only one ultimate debtor that was qualified and with a large scale. However, the repayments generally came directly from different child companies or projects. In order to control risk concentration and meet regulatory requirements better, the ABS portfolio was usually required to be build up from underlying assets with diversification to a certain level. For example, according to the region or project type of the direct debtors, the percentage of accounts payable in each type could not exceed a critical value. This kind of constraint was expressed as follows:

$$\max \left( \frac{\sum_{m=1}^{m_j} \text{BAL}_{mj}}{\sum_{i=1}^k \text{BAL}_i}, 1 \leq j \leq J \right) \leq \text{PAR}_{\text{ul}}, \quad (4)$$

where  $J$  was the number of assets categories and  $\text{BAL}_{mj}$  was the balance of accounts payable  $m$  in category  $j$  of selected assets.  $\text{PAR}_{\text{ul}}$  was the upper limit allowable for the proportion of accounts payable balances under each category.

*2.1.2. Objects in Smart Transportation Supply Chain ABS Portfolio Allocation.* Even if the requirements of those three basic constraints discussed above were met, it was still impossible to guarantee that the portfolio allocated was the best solution. For example, the size of the assets could be too small, which might lead to the lack of financing optimization effect. At the same time, it would not guarantee the optimization of asset diversification. Therefore, the following optimization objectives were added to the model.

(1) *Maximized Asset Size.* In order to improve the effect of financing optimization and alleviate the liquidity pressure of downstream entities in the supply chain, it was required to issue or circular purchase assets as large as possible to meet the upper limit of the scale. At the same time, the larger the purchase scale, the less the remaining funds in the special account and the lower the cost of keeping a balance with no interests in the trust account. The mathematical description of the optimization objective was shown as follows:

$$\begin{aligned} \text{Let } A \in Z_0, B \in Z_0, A \neq B, a \in A, b \in B, \\ \text{then } \text{sum}(\text{BAL}_a) \geq \text{sum}(\text{BAL}_b), \end{aligned} \quad (5)$$

where  $Z_0$  was the collection of all accounts payable portfolios that meet the constraints with  $A$  and  $B$  as any two unique portfolio collections belong to it. Let  $A$  be the collections of optimal portfolios but  $B$  not, with  $a$  as any one optimal portfolio in  $A$  and  $b$  as any one portfolio in  $B$  which was not optimal; then, the total balance of portfolio  $a$  should always be larger than  $b$ .

(2) *Maximized Asset Diversification.* Portfolio risks usually involved a factor positively related to the correlation coefficient of individual assets. The higher the homogeneity of assets, the higher the degree of portfolio risk. Therefore, to get optimal portfolio allocation, it was necessary to minimize the correlation between assets, that was, to improve the diversification of assets. The optimization object of diversification was expressed as follows with the strength of assets correlation denoted as  $\sigma$ :

$$\begin{aligned} \text{Let } A \in Z_0, B \in Z_0, A \neq B, (i, j) \in A, (k, l) \in B, \\ \text{then } \text{sum}(\sigma_{ij}) \leq \text{sum}(\sigma_{kl}), \end{aligned} \quad (6)$$

where  $Z_0$  was still a collection of all accounts payable portfolios that meet constraints,  $A$  was a collection of optimized accounts payable portfolio,  $B$  was a collection of nonoptimized portfolios different from  $A$ .  $(i, j)$ ,  $(k, l)$  are any pair of assets in  $A$  and  $B$ , respectively. Assets correlation strengths between  $(i, j)$ ,  $(k, l)$  were described as  $\sigma_{ij}$ ,  $\sigma_{kl}$ .

Finally, the portfolio should be as close as possible to the optimization objects described in (5) and (6) and satisfy constraints in (1)–(4).

*2.2. A GD-PSO Algorithm.* For the asset portfolio optimization of smart transportation supply chain ABS, the degree of asset diversification should always be considered; that was, the relationships between assets should be introduced

to the algorithm appropriately. A traditional method was to calculate the correlation coefficient between assets and to construct related terms in a function to quantify the relationships between assets. However, for accounts payable in supply chain finance, the relationships between them were difficult to quantify due to the lack of long-term, high-quality historical data. Another method was to calculate the Herfindahl–Hirschman Index (HHI), but the range of the coefficient was between  $(1/P, 1)$ , with  $P$  as the number of asset categories contained in the portfolio. Because the number of assets and the number of asset categories were likely to be different in different portfolios from every single iteration, there would be no strict comparability in HHI with the continuous adjustment of the portfolio during the process of optimization.

To solve those problems, we proposed an algorithm that integrated PSO and graph density theory (GD-PSO), which successfully solved the difficulty of measuring the relationships between underlying assets of smart transportation supply chain ABS. The two optimization objects of asset size and asset diversification were mixed into a single one, which could further improve the optimization results and the convergence speed of the PSO algorithm at the same time.

*2.2.1. Objective Function with Density Penalty Term Based on an Incomplete Graph.* The diagram in Figure 1 showed the relationships between liabilities belonging to the same or different categories (regions and debtors as examples), where the central nodes represent the debtor's regions, nodes in the middle layers represent the debtors, and outer nodes represent accounts payable (assets).

One type of debtor could correspond to one or more debtors, and one debtor could also correspond to one or more assets. In this incomplete graph, the number of edges connecting nodes could be used to define the GD of the nearby regions of those nodes. However, each asset has only one edge connected to the debtor to which it belongs and which was directly related to other assets. A debtor was also connected only to the region to which it belongs and which was directly connected to other debtors. In this situation, regions, debtors, and assets actually constituted a space of tree with three layers. The degree of association between assets could ultimately be traced back to the root node, that is, the similarities and differences between the debtor's region. Thus, the degrees of correlation between assets could be measured with the density of the region around the root node, that is, the sum of its edges. At the same time, because the number of liabilities under each debtor's name was different, these edges should have different weights, which could be quantified by the proportion of the number of assets under the debtor's name to the amount of the whole asset pool. After adjusting the density of the area around the root node to the weighted sum of the edges, the variable of density, which was recorded as  $D_{\text{root}}$ , was shown in the following function:

$$D_{\text{root}} = \frac{\sum_{c=1}^C \left( \sum_{i=1}^I a_{ci} \right) \times 1}{\sum_{i=1}^N a_i}, \quad (7)$$

where  $D_{\text{root}}$  was the relative weighted sum of the number of edges corresponding to the root node of asset category. Asset  $a$ , for example, was belonging to debtor  $c$ , and debtor  $c$  was belonging to region  $L$ , which was a node denoted as  $\text{node}_L$ . The number of edges connected to  $\text{node}_L$  was  $C$ , corresponding to the number of  $C$  debtors. The weight of each edge corresponded to the proportion of assets held by the debtor in the entire pool. The density of the surrounding area of the asset  $a$  was defined as the proportion of assets in a group formed by assets under the names of debtors in category  $L$  to all assets.

From the viewpoint of practical application, the density value was exactly equal to the proportion of the asset amount under the root node of its debtor's category to the whole parent pool, which was very intuitive and easy to understand. That was also meaningful because assets that belong to a category with a relatively large number and high balance of assets would be more likely to get the pooling of risk and in danger of having assets being default concurrently. For the optimal object of maximizing risk diversification, the degree of risk concentration should be punished in the process of iteration.

Considering the penalty term based on the GD defined above, the formula of the objective function with matrix operations was shown in the following:

$$\text{obj}(X_i) = wb \cdot \text{round}(X_i)' - (1 - w)D_{\text{root}} \cdot \text{round}(X_i)', \quad (8)$$

where  $b$  was an  $N$ -dimensional vector with the balance of each asset in the parent pool as an element,  $X_i$  was the solution of portfolio allocation in  $i$ th iteration,  $w$  was the weight related to the priorities of the objects in maximizing portfolio balance or diversification, and  $D_{\text{root}}$  was an  $N$ -dimensional vector representing the density around each asset, which was described in formula (7). The notation “ $\cdot$ ” represents the dot product of two vectors and  $\text{round}$  was the rounding function to round a number to the nearest integer.

Compared with the objective function of scale optimization in formula (5), the second term was added as the penalty term in formula (8), which would integrate the optimal object of scale and diversification and improve the convergence rate at the same time. Weight  $w$  was used to control the priority of objects in scale and diversification. The requirement of scale maximization was usually prior to diversification in portfolio allocation of smart transportation supply chain financial ABS, so  $w$  was usually set as a number close to 1. However, in order to ensure the significance of the penalty term,  $w$  should not be too large.

**2.2.2. GD-PSO Optimization Algorithm for Smart Transportation Supply Chain ABS Portfolio Allocation.** Based on the mathematical model and methods described above, the steps of the GD-PSO algorithm were as follows:

- (a) Let the whole parent pool as the search space, a certain number (recorded as  $M$ ) of portfolios were generated randomly as the starting position of the spatial search. With  $N$  as the number of assets in the parent pool, each portfolio was a vector of  $N$

dimensions. When a portfolio contained a certain asset, the corresponding element of the vector would be recorded as 1, else as 0. It should be noted that in order to improve the accuracy of the optimization algorithm, the integer programming problem was transformed into a noninteger problem, and the solution on each dimension was allowed to be numbers between 0 and 1 in the iterative process. When calculating the results of objective and constraint functions, numbers in the solution vector were rounded to the nearest integer; that is, if it was less than 0.5, the number was set to 0, else to 1. The initial portfolio was described as follows:

$$X_i = (x_i^1, x_i^2, \dots, x_i^N), \quad i = 1, 2, \dots, M, \quad (9)$$

where the solution of the portfolio allocation on asset  $n$  in the  $i$ th iteration was denoted as  $x_i^n$  and the vector of the solution in the  $i$ th iteration was  $X_i$ .

- (b) The optimal objective function value of each portfolio was calculated, and the positions of the best portfolio and swarm, with constraints met and minimum objective function value obtained in an iteration, were denoted as  $X_{\text{best}}$  and  $G_{\text{best}}$ , respectively. If there was no portfolio meeting constraint conditions in an iteration, one or multiple portfolios closest to the constraint condition would be selected, and then one portfolio with the minimum objective function value would be set as the best position. For two or more portfolios that obtain the minimum objective function value simultaneously, one of them would be selected as  $X_{\text{best}}$  randomly.
- (c) With the best individual and swarm position at  $X_{\text{best}}$  and  $G_{\text{best}}$ , other portfolio vectors in the space as probe particles would “fly” to them at the speed described in formula (10) to form a number of  $M$  new points in the  $N$ -dimensional space, which was another set of portfolio vectors for the next iteration, as shown in formula (11). Then, step  $b$  is repeated to get the optimal portfolio location  $X_{\text{best}}$  and the optimal portfolio swarms location  $G_{\text{best}}$  again for the next iteration.

$$v_{i+1} = w_{\text{pso}}v_i + c_1 * \text{rand}_1(p_{\text{best}_i} - x_i) + c_2 * \text{rand}_2(g_{\text{best}_i} - x_i). \quad (10)$$

$v_{i+1}$  was the velocity of particles in the  $i+1$ th iteration dependent on the velocity of last iteration with an inertial weight  $w_{\text{pso}}$ , on the distance to the best individual and swarm positions with learning weights  $c_1$  and  $c_2$ . Two  $u(0, 1)$  distributed random variables were denoted as  $\text{rand}_1$  and  $\text{rand}_2$ .

Then, the positions of the portfolios for the  $i+1$ th iteration should be as follows:

$$X_{i+1} = X_i + v_i. \quad (11)$$

- (d) Repeat steps  $b$  and  $c$ , until the convergence condition or the upper limit of the number of iterations is

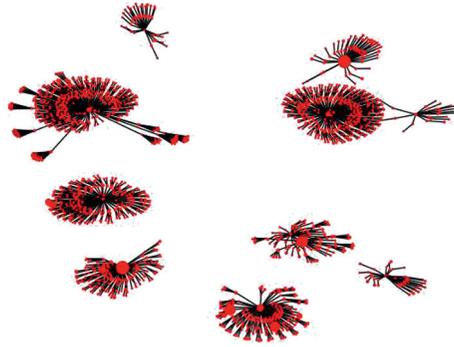


FIGURE 2: Asset relationships in parent asset pools.



FIGURE 3: Distributions of assets in the parent pool: balance of assets.

reached. Then, the optimal portfolio allocation was obtained.

### 3. Computational Experiments

According to the data of issued ABS, the parent asset pool composed of 1000 accounts payable was built with a total balance at 1.61368 billion yuan, weighted average life of 160.20 days, maximum percentage of a region assets at 26.40, and the maximum life at 604 days. In Figures 2 and 3, it was shown that the balance, life, and region of individual assets could vary largely in the parent pool, which was according to the characteristics of real static pools of smart transportation ABS underlying assets on the market. For example, the average balance was 1.61 million yuan, but with a standard deviation of 2.87 million yuan and minimum and maximum values at 0.50 and 69.77 million yuan, respectively. As to the lives of assets, the average value was 147.57 days, while the standard deviation reached 109.92 days and minimum and maximum values spread from 1 to 604 days.

At the same time, those sample assets were also copied and added to the initial asset pool and another two parent pools with 2000 and 3000 samples were formed. Those parent pools had a larger sample size but had the same

sample structure as the initial one. So, they were comparable to the initial one and could be used to test the performance of the algorithm in higher-dimensional spaces. The distribution of the parent pool was shown in Figures 2 and 3.

Formula (8) was applied as the objective function, while formulas (1), (3), (4) were as constraint functions. As to the life of the liabilities, because the legal period of supply chain ABS could be longer, for example, two years, all liabilities in the parent pool can meet the constraint requirement in (2) with the maximum life of 604 days. Therefore, the constraints in formula (2) are no longer added. Constraints and related thresholds were set as described in Table 1.

Set the number of points in the initial space  $N$  to be 50 and the minimum step of the objective function before search terminated to be  $10 e^{-8}$ . Since the elements in the final solution should be integers, the minimum step size of the best swarm's position could be appropriately amplified to 0.2. The inertial weight  $w$  was set to 0.5, while the learning factors of  $c_1$  and  $c_2$  were set to be 0.8. With those parameter settings, the steps of the GD-PSO algorithm described in 3 were followed and results were shown in Tables 2 and 3 and Figure 4.

Results in Table 2 show that, with the same samples, when objective and constraint functions were fixed, no

TABLE 1: Constraints and thresholds used in data validation.

Constraints	Variable name	Critical value		
		Sample size = 1000	Sample size = 2000	Sample size = 3000
Maximum amount of portfolio (10,000 yuan)	WTERM <sub>ul</sub>	100000	200000	300000
Weighted average life limit (days)	TBAL <sub>ul</sub>	150	150	150
Maximum percentage of a region (%)	PAR(location) <sub>ul</sub>	30	30	30
Maximum percentage of a debtor (%)	PAR(lender) <sub>ul</sub>	15	15	15

TABLE 2: Comparison of GD-PSO and PSO algorithm results.

Algorithm	Sample size	Maximum number of iterations	Optimal number of iterations	Total portfolio size (10,000 yuan)	Assets	Weighted average life (days)	The maximum percentage of a region	The maximum percentage of a debtor	Duration (s)
PSO	1000	100	No convergence	—	—	—	—	—	—
	1000	500	No convergence	—	—	—	—	—	—
	1000	2000	No convergence	—	—	—	—	—	—
	1000	19	No convergence	99998.79	563	141.80	28.05	5.50	9.61
GD-PSO	1000	100	19	99999.13	592	146.37	24.57	6.56	9.33

TABLE 3: GD-PSO performance testing of algorithms.

Algorithm	Sample size	Maximum number of iterations	Number of iterations to convergence	Total amount in portfolio (10,000 yuan)	Number of assets	Weighted average life of assets in the portfolio (days)	Maximum percentage of a region	Maximum percentage of a debtor	Time consumed to convergence (s)
GD-PSO	1000	100	19	99999.1303	592	146.37	24.57	6.56	9.337
	2000	100	22	193179.8014	1121	146.627	26.64	4.95	6.96
	3000	100	22	281108.8644	1618	148.777	26.40	3.05	7.44

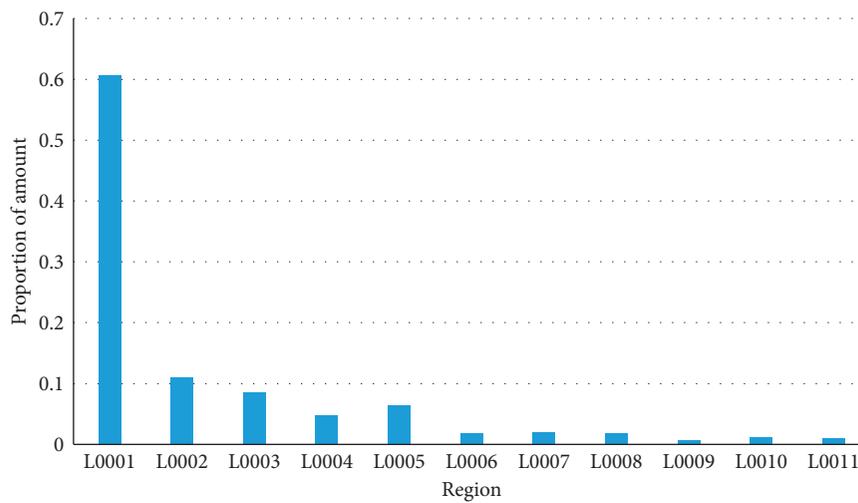


FIGURE 4: Distribution of assets among different regions.

convergence could be reached after 100 iterations in a 1000-dimensional space with a simple PSO algorithm, while the GD method was not introduced. Even if the

number of iterations was increased to 2000, the convergence result still could not be obtained. However, when the GD-PSO algorithm was applied, only 19 iterations were

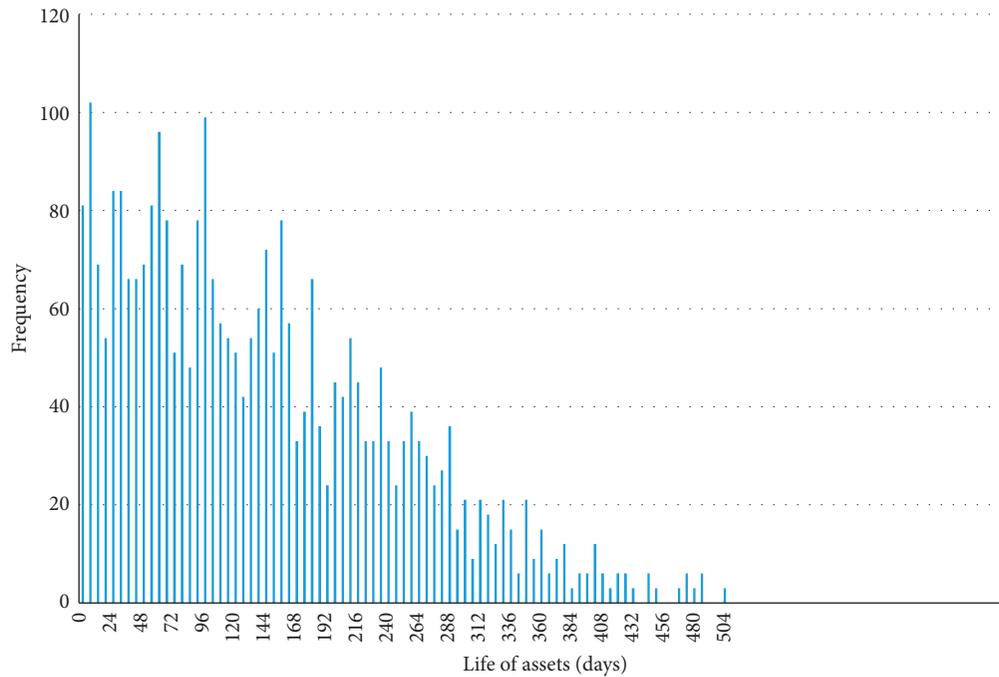


FIGURE 5: Distributions of assets in the parent pool: life of assets.

necessary to reach convergence. At the same time, when the number of iterations was kept the same, with the GD-PSO algorithm, the result of optimal portfolio balance (999,987,863 yuan, after 19 iterations) was better than that with the pure PSO algorithm (999,991,303 yuan, after 19 iterations). Regarding the degree of diversification, GD-PSO also showed advantages superior to PSO. It could also be found in Table 2 that with GD-PSO, the maximum percentage of assets in a region (24.57) was lower than the result of PSO (28.05). Moreover, in Figure 5, the result of pure PSO showed 9 visible root nodes, while the number for GD-PSO algorithm was 11. The number of assets connected to a single root node was increased in the diagram of GD-PSO (with an average number of 53.82 to 51.18 in PSO), which means that the degree of diversification in the optimal result of GD-PSO was improved. In terms of time performance, with the same number of iterations, GD-PSO algorithm still took less time than PSO. That could be related to the penalty term in the objective function of the GD-PSO algorithm, which could make the differences between portfolios more significant and then allocate the best solution of a nonlinear problem more efficiently.

As shown in Table 3, it was found that the performance of the GD-PSO algorithm was not significantly reduced by increasing the sample size of the parent asset pool from 1000 to 2000 or even 3000, while the sample structure, parameters, and constraint and objective functions were kept unchanged. Those results mean that in higher-dimensional spaces, the GD-PSO algorithm could still meet the requirements of supply chain ABS portfolio allocations and achieve optimal objects.

#### 4. Conclusions

In this article, portfolio optimization of smart transportation asset-backed securities was modeled as a high-dimensional

nonlinear optimization problem with multiple objects and constraints, and correlations between risky assets were considered. Based on particle swarm optimization algorithm, graph density measurement and penalty function were introduced and the GD-PSO algorithm was proposed. Compared with simple PSO, GD-PSO provided better optimal results with greatly improved computation efficiency. However, there were still some limitations with this method. For example, the graph density was calculated based on the whole parent asset pool and was a static measurement, while during the processes of spatial search and iteration, the vectors of portfolios were dynamic. To further improve the performance and accuracy of portfolio allocations for ABS in smart transportation ABS and other fields, in future studies, more investigation will be done regarding the density measurement in a dynamic space and its application in the optimization algorithm.

#### Data Availability

The data come from a supply chain financial technology company in China and cannot be made publicly available due to confidentiality requirements.

#### Conflicts of Interest

The authors declare that they have no conflicts of interest.

#### References

- [1] J. Du and X. Zhou, "Discussion on the possibility of asset securitization under supply chain finance," *Economic Research Guide*, vol. 10, no. 7, pp. 159-160, 2014.
- [2] L. Liang, "Actively promote supply chain innovation and application: analysis of supply chain asset securities," *Bonds*, vol. 7, no. 7, pp. 81-86, 2018.

- [3] S. Yang, "Investment and financing analysis PPP urban smart transportation monitoring system," *Construction Transport and Transportation*, vol. 33, no. 1, pp. 66-67, 2017.
- [4] X. Lei, "Discussion on accounting treatment of asset securitization," *China CPA*, vol. 5, pp. 91-95, 2017.
- [5] B. J. Keys, A. Seru, and V. Vig, "Lender screening and the role of securitization: evidence from prime and subprime mortgage markets," *Review of Financial Studies*, vol. 25, no. 7, pp. 2071-2108, 2012.
- [6] Lu, "Difficulties in design and operational countermeasures of circular purchase structure of asset securitization," *Shanghai Finance*, vol. 7, pp. 84-87, 2017.
- [7] S. Malamud, H. Rui, and A. Whinston, "Optimal incentives and securitization of defaultable assets," *Journal of Financial Economics*, vol. 107, no. 1, pp. 111-135, 2013.
- [8] Lu, "A practical application analysis of circular purchase structure of asset securitization," *Fujian Finance*, vol. 9, pp. 40-44, 2017.
- [9] T.-J. Chang, N. Meade, J. E. Beasley, and Y. M. Sharaiha, "Heuristics for cardinality constrained portfolio optimisation," *Computers & Operations Research*, vol. 27, no. 13, pp. 1271-1302, 2000.
- [10] A. Fernández and S. Gómez, "Portfolio selection using neural networks," *Computers & Operations Research*, vol. 34, no. 4, pp. 1177-1191, 2007.
- [11] J. Kennedy and R. C. Eberhart, "Particle swarm optimization," in *Proceedings of the IEEE International Conference on Neural Networks*, Perth, Australia, 1995.
- [12] T. Cura, "Particle swarm optimization approach to portfolio optimization," *Nonlinear Analysis: Real World Applications*, vol. 10, no. 4, pp. 2396-2406, 2009.