Portfolio selection model using teaching learning-based optimization approach

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ABSTRACT

Portfolio selection is among the most challenging processes that have recently increased the interest of professionals in the area. The goal of mean-variance portfolio selection is to maximize expected return with minimizing risk. The Markowitz model was employed to solve the linear portfolio selection problem (PSP). However, due to numerous constraints and complexities, the problem is so critical that traditional models are insufficient to provide efficient solutions. Teaching learning-based optimization (TLBO) is a powerful population-based nature-inspired approach to solve optimization problems. This article presents a portfolio selection model using the TLBO approach to maximize the portfolio's Sharpe ratio. The Sharpe ratio combines both expected return and risk. This algorithm models the natural teaching process of the classroom with two main phases, viz., teaching and learning. Performance analysis has been undertaken to investigate the suitability of TLBO based solution approach by comparing it with genetic algorithm (GA) and particle swarm optimization (PSO) on the real datasets, Deutscher Aktienindex (DAX) 100, Hang Seng 31, standard & poor's (S&P) 100, financial times stock exchange (FTSE) 100, and Nikkei 225. The empirical results verify the superiority of the TLBO over GA and PSO.

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1. INTRODUCTION

The activities needed to establish and manage a securities portfolio belong to portfolio management. It also employs analytical tools and theoretical models of optimal resource distribution. In general, portfolio management is known as a critical procedure that intends to make investments more profitable. Stock analysis, portfolio analysis, selection, evaluation, and portfolio revision are covered under it; portfolio selection is forming a portfolio that generates the best return for a given degree of risk. A portfolio having maximum return and minimum risk is called an optimum or efficient portfolio. The process of determining the optimum portfolio among various security combinations is called portfolio selection. Portfolio selection is the process of getting the proper equilibrium of the expected return and risk of the selected stock combination in the stock market. Various combinations of securities will provide different results. Desired objectives must be considered to make an optimum portfolio. The basic concept of portfolio management is diversification; the essence of diversification is "do not put all the eggs in one basket," which means never invest all your money in the same class of securities. Systematic diversification necessitates various parameters for various stocks, including their expected return, variance, and covariance between selected stocks' returns. Risk and return will be optimized as a result of diversification. Portfolio selection has different constraints such as boundary, budgetary, cardinality, liquidity, transaction lot, and transaction cost [1], [2].

In portfolio management, identifying the optimal mix of stocks available for fund deployment is an essential job for finance portfolio managers. Markowitz [2] proposed a model for portfolio selection in 1952; he said that if two portfolios have an equal expected return, investors should select the one with less risk between the two, and if two portfolios have the same risk, then he should go for one with more return. Investor rationality is the assumption of modern portfolio theory. A new model was proposed by Sharpe [3] that can evaluate a significant number of stocks cheaply; this approach is named the “Single index model.” Grootveld and Halarbach [4] studied the differences and similarities between using mean-return and downside risk measures as return and risk parameters in portfolio selection and compared them with the mean-variance model.

Solving such a problem is extremely difficult; many evolutionary approaches were presented to resolve the portfolio selection problem (PSP). Li [5] studied the optimal portfolio by genetic algorithm (GA). Shahid *et al.* [6] presented a PSP optimizing the Sharpe ratio by applying the stochastic fractal search (SFS) method motivated by the natural growth process based on the principle of the fractal theory; they have also applied the SFS method to solve the constrained risk-budgeted portfolio optimization model [7]. Wang *et al.* [8] solved the credit portfolio optimization problem with a multiobjective GA model. Adebiyi and Ayo [9] solved the extended mean-variance problem by an efficient metaheuristic method of generalized differential evolution 3 (GDE 3); this problem has four constraints and the results of this study showed improvement when compared with GA, PSO, simulated annealing (SA), and tabu search (TS). Hagströmer and Binner [10] solved the full-scale optimization (FSO) asset selection problem by a heuristic technique differential evolution; outcomes showed that if investors are sensitive to risk, the proposed approach bettered portfolio returns compared to mean-variance (MV) method.

Kamili and Riffi [11] proposed an optimization method named cat swarm optimization for PSP; this method is based on the cat family's behavior featured by observation mode and hunting mode. Kaucic [12] integrated risk parity with cardinality constrained portfolio selection model, and a multiobjective PSO algorithm solves this issue. Zhang [13] optimized the risk of the financial market with a PSO algorithm. Cura [14] presented a heuristic model for portfolio selection employing an artificial bee colony approach considering the weekly prices of indexes of different countries and found that the presented approach is superior to its peers. Zhao *et al.* [15] solved the multiobjective cardinality-constrained PSP by PSO.

The various nature-inspired algorithms can select an optimum portfolio, Moradi *et al.* [16] presented a multiobjective water cycle strategy to resolve the mean-variance PSP, and the proposed algorithm was found more effective than other algorithms. Strumberger *et al.* [17] presented a moth search approach for portfolio optimization. Shahid *et al.* [18] proposed an invasive weed optimization strategy for the risk-budgeted portfolio optimization problem by maximizing the Sharpe ratio. Mazumdar *et al.* [19] proposed grey wolf optimizer (GWO) for portfolio formation and risk optimization using Meta heuristic evolutionary optimization.

Akbay *et al.* [20] solved the cardinality-constrained PSP with a parallel variable neighborhood search approach. Shahid *et al.* [21] presented a new portfolio selection model by employing gradient-based optimization (GBO) to optimize the Sharpe ratio of the constructed portfolio. Shahid *et al.* [22] employed the GBO approach to resolve the PSP; this study's empirical investigation findings support the superiority of the suggested approach.

Some hybrid algorithms are also proposed by combining more than one algorithm to select optimum portfolios. Zaheer *et al.* [23] developed a metaheuristic technique with a PSO algorithm named hybrid particle swarm optimization (PSO) to optimize the portfolio, which has to mean return and variance of return as selection criteria. Konstantinou *et al.* [24] presented a hybrid optimization algorithm combining GA and sonar-inspired optimization approach, and the performance of this algorithm is studied with its contemporary approaches.

In this study, the authors presented a portfolio selection model by maximizing the Sharpe ratio, employing a new approach called the teaching-learning based optimization (TLBO) algorithm [25]. TLBO is a novel nature-inspired technique motivated by the teaching and learning process of a classroom. The contributions of the work are given,

- To employ the proposed TLBO approach in portfolio selection for optimizing the portfolio's Sharpe ratio. Portfolio’s expected return and risk are combined by the Sharpe ratio. Therefore, this is taken as the objective parameter to optimize the return and risk jointly.
- A comparative study has been conducted with the state-of-the-art approaches, namely, GA and PSO, from the literature.
- An empirical investigation has been done on the real benchmark datasets i.e., DAX 100, FTSE 100, Hang Seng 31, S&P 100, and Nikkei 225.

The remaining manuscript is discussed: In section 2, we presented in detail the mathematical representation of the PSP and TLBO Algorithm to maximize the Sharpe ratio. Section 3 presents the analysis outcomes with a comparative performance analysis. Finally, section 4 concludes the study.

2. SOLUTION MODEL

In this segment, the mathematical representation of the PSP is presented with TLBO based solution model. Equations for return, portfolio risk, and Sharpe ratio are explained in section 2.1. Further, TLBO algorithm as a solution model has also been discussed in detail in section 2.2.

2.1. Portfolio selection problem (PSP)

Portfolio selection is the process of selecting an optimum portfolio. The optimum portfolio is one that has an optimized value of the objective parameter (maximum return and minimum risk) at any given level. The ith portfolio (P) is designed with N stocks, $S = \{ S_1, S_{2,} \dots S_N\}$ with weight set, $W = \{ W_1, W_2, \dots W_N\}$. Respective expected returns of stocks are $\mathcal{R} = \{ R_1, R_2, \dots, R_N\}$. The mathematical formulation of expected returns and risk can be written as,

$$Return_P = \sum_{i=1}^{N} . W_i R_i \tag{1}$$

$$Risk_P = \sum_{i=1}^{N} . \sum_{j=1}^{N} . W_i W_j \, CV_{ij} \tag{2}$$

Now, the objective is to maximize the expected return ($Return_P$) and to minimize the portfolio risk ($Risk_P$). So, the Sharpe ratio (SR) is computed and optimized, which is the ratio of risk-free return to risk of the portfolio constructed. By optimizing the Sharpe ratio, both the return and risk are getting optimized. Sharpe ratio can be written,

$$SR = \frac{Return_P - R_f}{Risk_P} \tag{3}$$

Subject to constraints,

$$\sum_{i=1}^{n} W_i = 1 \tag{4}$$

$$0 \leq W_i \leq 1 \tag{5}$$

Where W_i is the proportion of funds invested in stock S_i, R_i refers to individual stock return. W_j represents the proportion of funds invested in S_j, and CV_{ij} denotes the covariance between the pair of i^{th} and j^{th} stock. R_f refers to risk-free return, considered zero due to an equity-based system. A repair procedure is applied to deal with these constraints. The constraints in the problem as described in (4) and (5) are linear, with a convex viable region. When the lower or upper boundaries are breached, the respective weights are substituted with the value of the lower or upper bounds. A normalization strategy is utilized to manage the budget constraints (a sum equal to 1), in which the weight of each stock is divided by the sum of the portfolio's aggregate weight.

2.2. TLBO algorithm

TLBO [25] is an approach that concentrates on the teacher's influence on the output of students in a classroom. The teacher works hard to educate all of the students in the class. The students then communicate to change and improve their newly acquired information. When we need to solve an issue, we usually use a random optimization method with some parameters that may be fine-tuned to assist us in finding the optimal global value as quickly as possible with the least effort and time. Other algorithms require specific algorithm factors such as inertia weight and specific coefficient, but the TLBO approach does not demand any algorithm-specific factors.

Assume two separate teachers in two different courses are teaching the same subject with the same contents to the same competence level students. In this case, we will use a class (Population P) with a specific number of students and subjects (decision variables of an optimization method) from which they will learn. The value we need to optimize is the outcome of a student in an exam (Fitness). A good teacher improves the average of the student's results. Learners also benefit from their interactions with one another, which increases their performance.

A quantitative approach is developed and executed for solving PSP using the teaching-learning process, and this results in a new optimization model named TLBO. The best learner is deemed a teacher since he or she is seen as the most known individual in society. The teacher appears to be trying to disperse knowledge among students, which raises the overall competence of the class and aids learners in receiving good grades. Consequently, the teacher increases the class's average according to his abilities, and the population's mean value determines the quality of students.

TLBO is a population-based approach that progresses to the global answer through candidates of solutions. In TLBO, the population refers to a learners' class; in optimization, the population has distinct decision variables; in TLBO, the subjects presented to learners are decision variables; and the learners' outcome is regarded as "fitness," as in other population-based optimization approaches. The best solution identified so far is deemed a teacher [25]. The teacher phase and learner phase are two parts of the TLBO approach; the first part entails learning from a teacher, while the second part entails learning from one another respectively. The steps are,

Step 1: Defining the problem and starting its variables

Initially, the optimization problem started with the following variables; the population size (P_n), number of generations (Gen_{max}), the number of decision variables (*N)*, and their constraints. The problem is to maximize Sharpe ratio (*SR*). Now teaching- learning based optimization algorithm is used to maximize SR which is the objective function as explained in (3) for the decision variable (Weights) such that $L \leq W_i \leq U$ subject to constraints described by (4) to (5).

Step 2: Selecting a population

Make a random population considering the size of the population and the number of decision variables. The population (Class) size in TLBO refers to the number of students (Learners); in portfolio selection, stock combination or portfolios work as learners, whereas the proportion of stocks (W_i) refers to the subjects that students are taught. This population is demonstrated; $Class = \{ L_1, L_2, L_3, \ldots, L_{P_n}\}$, and each learner ($L_j$) has *N* number of subjects (stocks). In the designed portfolio, each stock has an allotted weight to a particular stock (W_i) which is the proportion of the total investment or fund. We have to be optimized the result (Sharpe ratio) of the learners (Portfolios).

Step 3: Teacher phase

In the teacher phase, since a teacher is the most expert in class. He provides information to the whole class and attempts to improve the competence level of the class up to his level. For each learner, the mean calculation for the kth subject or weight (M_k) is,

M_k= Sum of weights (W_k) / Number of weights (N)

At first, the Sharpe ratio (SR_j) of each learner in the class (L_j: $j = 1, 2, .. P_n$) has been computed. The topper among all learners in the specific class is taken as a teacher (T_g) for the g^{th} generation according to the (6). Then, the difference mean for each subject is calculated by the (7),

$$T_g = \underset{\max(SR_j : j=1,2,..P_n)}{L_j} \tag{6}$$

$$DM_k = r_k \left(T_g - TF * M_k\right) \tag{7}$$

Where M_k is the mean of the respective weights allotted to respective stocks in each portfolio, r_k is an arbitrary value in the range (0-1), and *TF* is the teaching factor that determines the mean value to be modified. *TF* will be 1 or 2 calculated as per (8). The value of the current solution is updated by adding the difference mean by using (9).

$$TF = round\left(1 + rand\ (0,1)\right) \tag{8}$$

$$L_{new} = L_{old} + DM_k \tag{9}$$

Where L_{new} is a new weight, L_{old} is the old weight, DM_k is the difference mean of the particular subjects, and it is calculated as per (7). Now, apply the repairing procedure discussed in section 2.1 to satisfy the constraints given in (4) and (5). Accept L_{new} if it provides a better value of the Sharpe ratio.

Step 4: Learner phase

It is a process where learners enhance their knowledge through the interaction between themselves. Learners interact with themselves in formal and informal communication. If two learners interact, then we have to compare their fitness values. Knowledge transfer will take place from one who has more knowledge to one who has less knowledge. A learner (stock) with more fitness value (better Sharpe ratio) is considered more knowledgeable. For $i = P_n$ randomly select two learners (Portfolios), L_X and L_Y, with W_X and W_Y weights (Subjects), respectively, in portfolios where $W_X \neq W_Y$. The learner phase includes the following steps:

for each generation
if $SR(L_X) > SR(L_Y)$, then
New L_X = Old $L_X + r_k (L_X - L_Y)$
else
New L_X = Old $L_X + r_k (L_Y - L_X)$
end if
end for

where L_X and $L_Y \in$ Class, and r_k is the random number used in difference mean calculation. Again, apply the repairing procedure to satisfy the constraints. Then, calculate the fitness value for all randomly selected interactions between portfolios (learners). Compare the fitness value (Sharpe ratio) of the learner phase with those of the teacher phase and keep only the best fitness value (Sharpe ratio) and their corresponding weights. TLBO algorithm's learner phase and one generation are now complete [25].

Step 5: Terminating criteria

If the TLBO process is followed to the maximum number of generations, then stop; if not, start with the teacher phase of this approach again. This approach's procedure and mathematical calculation must be done again. This will be followed upto the maximum number of iterations.

Algorithm: TLBO

```
Input: Initialize N or P (number of learners) and W (number of decision variables or
subjects offered)
Output: The teacher T_g
TLBO ( )
 Start
   Initialize learner's population, generation (g), Gen_max
   Repair learners                                   // Satisfy the portfolio cobstraints
   Evaluate the fitness value                        // as per (3)
   Find M_k of all weights (subjects)
   Find T_g among all portfolios
   while (g ≤ Gen_max)
       for all learners                               ***Teacher phase ****
             Find TF                                    // Teaching factor as per (8);
             Update all learners                   // according to (9)
       end for
       Repair all learners                          // Satisfy all Portfolio constraints
       Evaluate fitness value                     // for the new learners;
          Accept better learner
          for all learners                             **Learner phase**
              Selection of learners randomly
              Update learners                       // as per Learner phase
          end for
         Repair learners                             // Satisfy the Portfolio Constraints
         Accept new, better learner
         Update  T_g and Mean M_k
         g = g+1
   end while
   End
```

3. RESULTS AND DISCUSSION

Simulation outcomes of the PSP using the TLBO, PSO, and GA approaches are discussed here. TLBO-based solution model is implemented in MATLAB R2016 on an Intel(R) i7-8700 CPU @ 3.20GHz, 64 GB RAM. For analysis, weekly returns from March 1992 to September 1997 have been taken of different benchmark datasets from DATASTREAM, which is shown in Table 1. The variables for the TLBO, PSO, and GA for performance analysis are given in Table 2, where P_n represents population size, Gen_{max} refers to maximum number of generations, *TF* is the teaching factor, in PSO *W* is inertia weight, wdamp is the inertia weight damping ratio, C1 and is personal learning coefficient, C2 is global learning coefficient.

In the analysis, 20 runs were performed to find the optimum values by the presented algorithm, as given in Table 2. Afterward, the maximum, minimum, mean, and standard deviation values were calculated for all the methods, viz. TLBO, PSO, and GA. The maximum (Max), minimum (Min), mean values (Avg.), and standard deviation (Stdeva.) of the Sharpe ratio (SR) of obtained values by various approaches are presented in Table 3. The best values of all approaches are highlighted in Table 3. It is clear from Table 3; that TLBO outperformed GA and PSO for the average and maximum value of the SR for all benchmark data sets. TLBO has the best standard deviation of the SR in Hang Seng 31 and Nikkei 225.

Table 1. Datasets information

Dataset Name	Country
DAX 100	Germany
Hang Seng 31	Hong Kong
FTSE 100	United Kingdom
S&P 100	United State of America
Nikkei 225	Japan

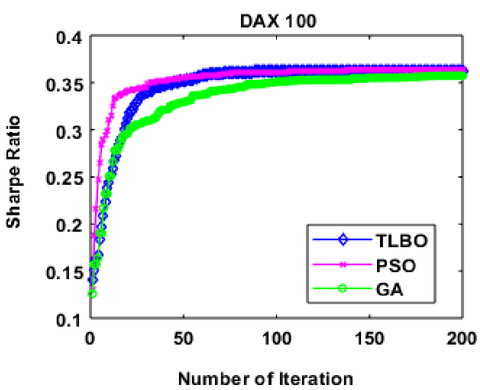
Table 2. Control parameters of TLBO, PSO, and GA approaches

Approach	Variables Specifications
Common variables	P_n = 100, Gen_{max}= 200
TLBO	TF = 1
PSO	W = 0.61, wdamp= 0.65, C1= 1.50, C2= 1.50
GA	Crossover = 0.6, Mutation = 0.4

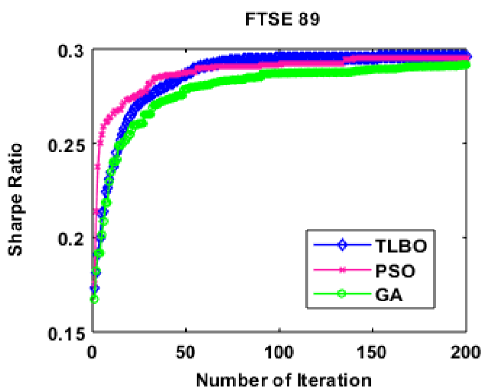
Table 3. Sharpe ratio

		GA	PSO	TLBO
DAX 100	Avg.	0.357915749	0.363599432	**0.363679577**
	Min	0.3554731	**0.363293116**	0.362915216
	Max	0.359630455	0.363724892	**0.36378147**
	Stdeva.	0.001199086	**0.000119509**	0.000259935
FTSE 89	Avg.	0.290621643	0.295422191	**0.295441564**
	Min	0.28838111	**0.294592118**	0.293517552
	Max	0.292239478	0.2955872	**0.295629474**
	Stdeva.	0.001199842	**0.000243871**	0.000480469
Hang Seng 31	Avg.	0.210439331	0.210441926	**0.210441927**
	Min	0.210434394	0.210441924	**0.210441927**
	Max	0.210441434	0.210441927	**0.210441927**
	Stdeva.	1.62212E-06	6.72608E-10	**3.00185E-13**
S&P 98	Avg.	0.311567237	0.319263852	**0.319364628**
	Min	0.314813385	**0.318316026**	0.316400852
	Max	0.308486534	0.319534931	**0.319658116**
	Stdeva.	0.001571972	**0.000344387**	0.000724699
Nikkei 225	Avg.	0.079219291	0.120587738	**0.136109327**
	Min	0.060937539	0.090464204	**0.127281168**
	Max	0.093606976	0.136277644	**0.139262038**
	Stdeva.	0.008831239	0.011508149	**0.004119606**

The converging tendency of TLBO, PSO, and GA demonstrate the optimum value of the Sharpe ratio for various generations as presented in Figures 1(a)-(e) as shown in Appendix, for DAX 100, FTSE 100, Hang Seng 31, S&P 100, Nikkei 225 benchmark datasets, respectively. TLBO has superior convergence features, such as convergence efficiency and objective value, as presented for the datasets. The outcomes presented in Table 3 and Figures 1(a)-(e) show that the proposed TLBO method outperformed PSO and GA methods for the considered PSP. Thus, we can interpret that the presented method contributes significantly to optimum portfolio selection.



(a)



(b)

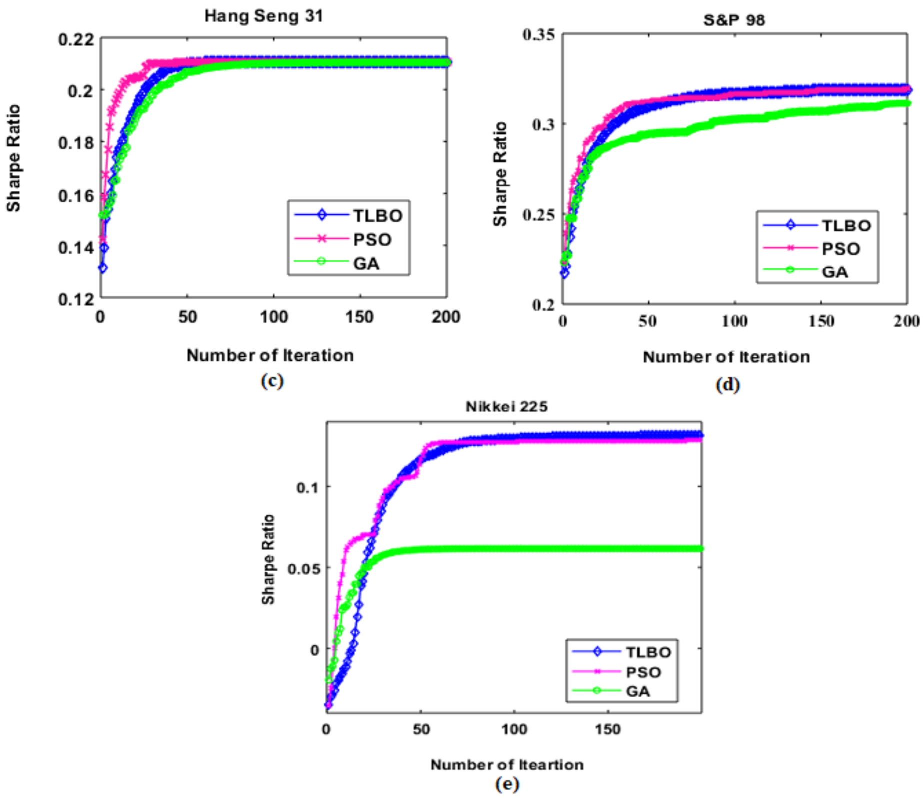


Figure 1. Convergence graph of TLBO, PSO, and GA on (a) DAX 100, (b) FTSE 89, (c) Hang Seng 31, (d) S&P 98, and (e) Nikkei 225

4. CONCLUSION

Portfolio selection has long been an important strategy for investors in capital markets. As a result, this study has proposed a solution for the PSP that uses a (TLBO) model that is quite effective in other disciplines. The goal of the approach is to obtain the highest Sharpe ratio of the portfolio. The proposed TLBO approach was developed to identify the best Sharpe ratio for the PSP. A repairing procedure technique is used to control constraints. Experimental analysis has been undertaken to evaluate TLBO based solution approach by comparing it with GA and PSO on real benchmark datasets. According to an experimental investigation, the TLBO solution outcomes are almost superior to the GA and PSO solution results.

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