# Chapter 9
# Optimal Portfolio Selection with Particle Swarm Algorithm: An Application on BIST-30

**Burcu Adıgüzel Mercangöz and Altaf Q. H. Badar**

**Abstract** Optimization is to find the best-performing solution under the constraints given. It can be something better by optimization process. Heuristic algorithm is an optimization algorithm which depends on natural events. The algorithms are simple and easy to implement for the researcher. The portfolio optimization is a process to find a solution to select the most appropriate combination between all financial assets under certain expectations and constraints. While solving portfolio optimization problems, the aim is to create portfolios by selecting the assets that provide the highest return from huge numbers of financial assets at a certain risk level or provide the lowest risk at a certain level of return. This chapter aims to examine the optimum portfolio with minimum risk by using the particle swarm optimization (PSO) technique, for the stocks in the BIST-30 index. Logarithmic returns are calculated using the price data of the stocks. By using these returns, the optimum portfolio with minimum risk is created with PSO and nonlinear GRG (generalized reduced gradient) techniques. The empirical results obtained indicate that both methods give similar results.

**Keywords** Optimization · Particle swarm optimization (PSO) · Portfolio optimization · Markowitz portfolio theory · Heuristics · Swarm intelligence

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## 9.1 Introduction

Particle swarm optimization (PSO) is one of the intuitive techniques. This technique was first introduced by researchers James Kennedy and Russell Eberhart in the 1990s to find optimum solutions to nonlinear numerical problems inspired by the collective movements of fish and bird flocks (Eberhart & Kennedy, 1995). The technique has evolved since then in several ways. The technique itself was improved through several publications by the duo of Shi and Eberhart (2008). As the robustness of the technique was proved, it was implemented and researched in many publications. PSO not only sees variations but also has a lot of hybrid versions introduced, along with different optimization techniques.

PSO works on a swarm of particles. A single particle represents a probable solution to the optimization problem. The particles move in the search space based on their respective velocities. The velocity of a particle is dependent on its own inertia, for instance, its own previous velocity, individual best, and global best. Individual best is the best position that a particular particle has achieved until the current iteration, while the global best is the best position occupied by any of the particles from within the swarm. Each particle in PSO can be mapped to a fitness function. As the particle moves in the search space, its fitness function also changes. PSO tries to obtain the optimal position in the search space through the movement of particles. Some of the factors that affect the movement of particles in the swarm are constriction factor, random factors, inertia constant, etc. These factors are responsible for the explorative and exploitative behavior of the swarm.

The portfolio optimization problem is related to how investors will allocate their wealth among various assets. Therefore, portfolio optimization problems have been an important research area in modern finance and risk management. In this study, the PSO technique issued for optimum solutions of the Markowitz mean-variance model in the portfolio selection problem. Optimal portfolios are created according to the PSO and nonlinear generalized reduced gradient (GRG) techniques by using the logarithmic return data between June 2016 and July 2018 for 25 stocks within the BIST-30 index. Then, the coefficients of variation are calculated, with the risks and returns that are obtained. The coefficients of variation of the two techniques are similar. It has similar results, and PSO can thus be used as an alternative for solving portfolio optimization problem. Since quite similar results are obtained from two different techniques, it also proves the reliability of the techniques.

## 9.2 Portfolio Optimization and Mathematical Model

Investors are willing to get the highest return at a given level of risk or are willing to take the lowest risk at a given level of return. This is the portfolio optimization problem, which arises from the desire to maximize return while minimizing the investor's risk. In the stated balance, the best solution tried to be reached. The Markowitz mean-variance model is described below.

The expected return of the risky portfolio $E(Rp)$ is estimated as Eq. (9.1).

$$E(R_P) = W_A * R_A + W_B * R_B \tag{9.1}$$

$R_A$ and $R_B$ are the returns of two risky assets, $R_P$ is the portfolio return, and $W_A$ and $W_B$ are the weights of $A$ and $B$ in the risky portfolio, respectively, with two risky assets.

The variance of the two assets' risky portfolio is calculated as shown in Eq. (9.2).

$$\sigma_p^2 = W_A^2\sigma_B^2 + W_B^2\sigma_B^2 + 2W_A W_B \mathrm{Cov}(R_A, R_B) \tag{9.2}$$

The standard deviations of the two risky assets are $\sigma_A$ and $\sigma_B$. The covariance between assets $A$ and $B$ is $\mathrm{Cov}(R_A,R_B)$.

This is a just an example for two-asset risky portfolio. This can be extended to risky portfolios with more than two assets. Eq. (9.3) shows the estimation of expected return $E(R_p)$ of a risky portfolio of multiple assets. The estimation of standard deviation ($\sigma_P$) of a multiple-asset risky portfolio uses covariance matrix of all assets in the portfolio. Portfolio returns of multiple assets depend on the risky assets' own returns and the weights that describe how the portfolio investment is split. Therefore, expected return for "$n$" assets is calculated as below:

$$E\left(R_p\right) = \sum_{i=1}^{n} E(R_i) \tag{9.3}$$

where $n$ is the number of securities. The return is being finding by compute the weighted average returns of each security included in the portfolio. Portfolio risk also can be calculated using the weights and covariances of each asset in the risky portfolio as given in Eq. (9.4):

$$\mathrm{Var}\left(R_p\right) = \sigma_p^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} W_i W_j \mathrm{Cov}\left(R_i R_j\right) \tag{9.4}$$

The mathematical indication of portfolio optimization problem by using the Markowitz mean-variance model is shown in the nonlinear programming model as below. Equation (9.5) describes the objective function, while Eq. (9.6) represents the constraint associated with the objective function.

### 9.2.1 Objective Function

$$\text{Min.Var}\left(R_p\right) = \sigma_p^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} W_i W_j \text{Cov}\left(R_i R_j\right) \tag{9.5}$$

### 9.2.2 Constraints

$$\sum_{i}^{n} W_i = 1 \tag{9.6}$$

$$0 \leq W_i \leq 1 \; i = 1, 2, \ldots n.$$

The constraints mean that the assets in the portfolio cannot be in short positions.

## 9.3 A Portfolio Optimization Application by Using PSO Algorithm

A basic application of the PSO technique is applied for the Markowitz mean-variance model with stocks of BIST-30 index for the period from June 2016 and July 2018. The data is obtained from www.investing.com. The daily data is used and analyzed for 25 common stocks in the index since the data availability and being able to equalize periods for all stocks.

Coding and running of PSO is done by MATLAB. The information of these 25 stocks in the BIST-30 index traded on the Istanbul Stock Exchange is as in Table 9.1.

Daily data between June 2016 and July 2018 is used for these 25 stocks in BIST-30. Logarithmic returns are calculated with 503 daily observations using Eq. (9.7).

$$R_t = \ln\left(P_t / P_{t-1}\right) \tag{9.7}$$

Table 9.2 shows the log returns, variance, and standard deviation of the stocks. The variance-covariance matrix is as shown below in Table 9.3.

**Table 9.1** 25 Stocks in BIST-30: Code and company names used in the application

| | Code | Company name (*Original Turkish names from public disclosure platform) |
|---|---|---|
| 1 | AKBNK | AKBANK T.A.Ş. Unvanı |
| 2 | ARCLK | ARÇELİK A.Ş. |
| 3 | ASELS | ASELSAN ELEKTRONİK SANAYİ VE TİCARET A.Ş. |
| 4 | BIMAS | BİM BİRLEŞİK MAĞAZALAR A.Ş. |
| 5 | DOHOL | DOĞAN ŞİRKETLER GRUBU HOLDİNG A.Ş. |
| 6 | KOZAA | KOZA ANADOLU METAL MADENCİLİK İŞLETMELERİ A.Ş. |
| 7 | HALKB | TÜRKİYE HALK BANKASI A.Ş. |
| 8 | GARAN | TÜRKİYE GARANTİ BANKASI A.Ş. |
| 9 | ISCTR | TÜRKİYE İŞ BANKASI A.Ş. |
| 10 | SISE | TÜRKİYE ŞİŞE VE CAM FABRİKALARI A.Ş. |
| 11 | SAHOL | SABANCI HOLDING |
| 12 | KRDMD | KARDEMİR KARABÜK DEMİR ÇELİK SANAYİ VE TİCARET A.Ş. |
| 13 | TKFEN | TEKFEN HOLDİNG A.Ş. |
| 14 | TAVHL | TAV HAVALİMANLARI HOLDİNG A.Ş. |
| 15 | PETKM | PETKİM PETROKİMYA HOLDİNG A.Ş. |
| 16 | TOASO | TOFAŞ TÜRK OTOMOBİL FABRİKASI A.Ş. |
| 17 | SODA | SODA SANAYİİ A.Ş. |
| 18 | THYAO | TÜRK HAVA YOLLARI A.O. |
| 19 | TCELL | TURKCELL İLETİŞİM HİZMETLERİ A.Ş. |
| 20 | TUPRS | TÜPRAŞ-TÜRKİYE PETROL RAFİNERİLERİ A.Ş. |
| 21 | VAKBN | TÜRKİYE VAKIFLAR BANKASI T.A.O. |
| 22 | YKBNK | YAPI VE KREDİ BANKASI A.Ş. |
| 23 | EREGL | EREĞLİ DEMİR VE ÇELİK FABRİKALARI T.A.Ş. |
| 24 | TTKOM | TÜRK TELEKOMÜNİKASYON A.Ş. |
| 25 | KCHOL | KOÇ HOLDİNG A.Ş. |

Source: KAP Public Disclosure Platform

## 9.4 Portfolio Optimization by Using PSO Algorithm

The problem of portfolio optimization is solved through the implementation of PSO. The implementation of PSO is realized as indicated in the flowchart of Fig. 9.1. Figure 9.1 shows how the problem is solved stepwise. In the first step, the problem is defined, and data required for solving the problem are gathered. Data related to various stocks is also to be collected in the initial step. Next the problem is formulated according to the Markowitz mean-variance model along with the data available. The data available initially is raw and requires to be processed to form different matrices as shown in the previous section. In the problem, the Markowitz mean-variance model is the fitness function that is to be optimized. After formulating the problem, the coding is done. The most common version of PSO is implemented (Clerc, 1999). The Markowitz mean-variance model and PSO are coded using MATLAB. The coding of PSO should also be accompanied by the debugging of

**Table 9.2** Return, variance, and standard deviation of the 25 stocks

| | AKBANK | ARCLK | ASELS | BIMAS | DOHOL | KOZAA | HALKB | GARAN | ISCTR |
|---|---|---|---|---|---|---|---|---|---|
| Average log return | −0.00013 | −0.00053 | 0.002065 | 0.000349 | 0.001486 | 0.00373 | −0.0004 | 0.000264 | 0.000314 |
| Standard deviation | 0.017606 | 0.015514 | 0.024001 | 0.014477 | 0.031727 | 0.043822 | 0.023784 | 0.018751 | 0.0179 |
| Variance | 0.00031 | 0.000241 | 0.000576 | 0.00021 | 0.001007 | 0.00192 | 0.000566 | 0.000352 | 0.00032 |
| | SISE | SAHOL | KRDMD | TKFEN | TAVHL | PETKM | TOASO | SODA | THYAO |
| Average log return | 0.001005 | −8.8E-05 | 0.002446 | 0.002098 | 0.001284 | 0.000695 | 1.18E-05 | 0.001634 | 0.001751 |
| Standard deviation | 0.015689 | 0.014818 | 0.026747 | 0.260214 | 0.021248 | 0.018614 | 0.01592 | 0.015351 | 0.024391 |
| Variance | 0.000246 | 0.00022 | 0.000715 | 0.067712 | 0.000451 | 0.000346 | 0.000253 | 0.000236 | 0.000595 |
| | TCELL | TUPRS | VAKBN | YKBNK | EREGL | TTKOM | KCHOL | | |
| Average log return | 0.000315 | 0.001431 | 0.000184 | −6.7E−05 | 0.001878 | –0.00104 | 0.000118 | | |
| Standard deviation | 0.015905 | 0.016677 | 0.019914 | 0.019309 | 0.020898 | 0.020677 | 0.016515 | | |
| Variance | 0.000253 | 0.000278 | 0.000397 | 0.000373 | 0.000437 | 0.000428 | 0.000273 | | |

**Table 9.3** Variance-covariance matrix of the 25 stocks

| | AKBANK | ARCLK | ASELS | BIMAS | DOHOL | KOZAA | HALKB | GARAN | ISCTR | SISE | SAHOL | KRDMD | TKFEN - | TAVHL | PETKM | TOASO | SODA | THYAO | TCELL | TUPRS | VAKBN | YKBNK | EREGL | TTKOM | KCHOL |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AKBANK | **0,0003106** | -0,0000131 | 0,0000129 | 0,0000387 | 0,0001849 | 0,0002094 | 0,0000185 | 0,0002876 | -0,0000243 | -0,0000128 | 0,0001693 | -0,0000068 | 0,0002366 | 0,0001424 | -0,0000232 | 0,0000058 | -0,0000192 | 0,0000235 | 0,0000152 | 0,0000827 | 0,0002733 | 0,0002566 | -0,0000195 | -0,0000086 | -0,0000119 |
| ARCLK | -0,0000131 | **0,0002412** | 0,0000519 | 0,0000060 | -0,0000162 | -0,0000590 | 0,0000001 | -0,0000111 | 0,0000107 | 0,0000024 | -0,0000127 | 0,0000172 | -0,0003083 | -0,0000160 | 0,0000123 | 0,0000025 | 0,0000043 | 0,0000004 | -0,0000120 | -0,0000031 | -0,0000105 | -0,0000250 | 0,0000158 | -0,0000159 | 0,0000396 |
| ASELS | 0,0000129 | 0,0000519 | **0,0005772** | 0,0000167 | -0,0000133 | -0,0000290 | 0,0000669 | -0,0000085 | -0,0000133 | 0,0000198 | -0,0000193 | 0,0000183 | 0,0001848 | 0,0000050 | -0,0000062 | 0,0000061 | 0,0000174 | -0,0000127 | -0,0000070 | -0,0000150 | -0,0000101 | -0,0000050 | -0,0000015 | -0,0000130 | 0,0000079 |
| BIMAS | 0,0000387 | 0,0000060 | 0,0000167 | **0,0002100** | 0,0000028 | 0,0000238 | -0,0000182 | 0,0000294 | 0,0000037 | -0,0000092 | 0,0000115 | -0,0000073 | -0,0001761 | 0,0000128 | 0,0000339 | -0,0000065 | 0,0000034 | -0,0000146 | 0,0000606 | -0,0000038 | 0,0000366 | 0,0000219 | -0,0000056 | -0,0000090 | 0,0000030 |
| DOHOL | 0,0001849 | -0,0000162 | -0,0000133 | 0,0000028 | **0,0010086** | 0,0003230 | 0,0000172 | 0,0002104 | -0,0000002 | -0,0000195 | 0,0001347 | -0,0000540 | 0,0002124 | 0,0001491 | -0,0000333 | -0,0000139 | -0,0000273 | -0,0000052 | -0,0000194 | 0,0001046 | 0,0001913 | 0,0001973 | -0,0000454 | -0,0000485 | -0,0000471 |
| KOZAA | 0,0002094 | -0,0000590 | -0,0000290 | 0,0000238 | 0,0003230 | **0,0019242** | -0,0000384 | 0,0002247 | -0,0000544 | -0,0000669 | 0,0001522 | -0,0000110 | 0,0002349 | 0,0002520 | 0,0000000 | -0,0000448 | -0,0001021 | 0,0001058 | 0,0000323 | 0,0000730 | 0,0002468 | 0,0002561 | -0,0000412 | 0,0000179 | -0,0000603 |
| HALKB | 0,0000185 | 0,0000001 | 0,0000669 | -0,0000182 | 0,0000172 | -0,0000384 | **0,0005668** | 0,0000157 | -0,0000173 | -0,0000007 | 0,0000025 | 0,0000015 | 0,0002129 | 0,0000044 | -0,0000053 | -0,0000079 | -0,0000194 | -0,0000049 | 0,0000087 | -0,0000153 | 0,0000214 | -0,0000012 | -0,0000187 | -0,0000057 | 0,0000226 |
| GARAN | 0,0002876 | -0,0000111 | -0,0000085 | 0,0000294 | 0,0002104 | 0,0002247 | 0,0000157 | **0,0003523** | -0,0000139 | -0,0000132 | 0,0001711 | -0,0000254 | 0,0002101 | 0,0001413 | -0,0000243 | 0,0000178 | -0,0000215 | 0,0000160 | 0,0000145 | 0,0000939 | 0,0002903 | 0,0002733 | -0,0000206 | -0,0000096 | -0,0000212 |
| ISCTR | -0,0000243 | 0,0000107 | -0,0000133 | 0,0000037 | -0,0000002 | -0,0000544 | -0,0000173 | -0,0000139 | **0,0003211** | -0,0000226 | -0,0000077 | -0,0000203 | 0,0001092 | 0,0000083 | 0,0000144 | 0,0001094 | 0,0000123 | -0,0000094 | 0,0000053 | -0,0000138 | -0,0000291 | -0,0000098 | 0,0000062 | 0,0000048 | 0,0000158 |
| SISE | -0,0000128 | 0,0000024 | 0,0000198 | -0,0000092 | -0,0000195 | -0,0000669 | -0,0000007 | -0,0000132 | -0,0000226 | **0,0002466** | -0,0000112 | -0,0000116 | -0,0000443 | -0,0000344 | 0,0000302 | -0,0000045 | -0,0000064 | -0,0000283 | 0,0000186 | -0,0000200 | -0,0000173 | -0,0000219 | 0,0000058 | 0,0000062 | 0,0000109 |
| SAHOL | 0,0001693 | -0,0000127 | -0,0000193 | 0,0000115 | 0,0001347 | 0,0001522 | 0,0000025 | 0,0001711 | -0,0000077 | -0,0000112 | **0,0002200** | -0,0000141 | 0,0001282 | 0,0001016 | -0,0000150 | 0,0000014 | -0,0000270 | 0,0000163 | 0,0000045 | 0,0000672 | 0,0001683 | 0,0001764 | -0,0000107 | -0,0000001 | -0,0000051 |
| KRDMD | -0,0000068 | 0,0000172 | 0,0000183 | -0,0000073 | -0,0000540 | -0,0000110 | 0,0000015 | -0,0000254 | -0,0000203 | -0,0000116 | -0,0000141 | **0,0007168** | 0,0004420 | 0,0000037 | -0,0000073 | -0,0000070 | -0,0000068 | 0,0003245 | 0,0000112 | 0,0000103 | -0,0000249 | -0,0000244 | 0,0000024 | -0,0000161 | 0,0000193 |
| TKFEN - | 0,0002366 | -0,0003083 | 0,0001848 | -0,0001761 | 0,0002124 | 0,0002349 | 0,0002129 | 0,0002101 | 0,0001092 | -0,0000443 | 0,0001282 | 0,0004420 | **0,0678467** | 0,0000806 | -0,0001557 | -0,0000771 | -0,0000232 | 0,0007100 | -0,0000622 | -0,0001218 | 0,0003190 | 0,0001626 | -0,0003847 | 0,0000758 | -0,0000044 |
| TAVHL | 0,0001424 | -0,0000160 | 0,0000050 | 0,0000128 | 0,0001491 | 0,0002520 | 0,0000044 | 0,0001413 | 0,0000083 | -0,0000344 | 0,0001016 | 0,0000037 | 0,0000806 | **0,0004524** | -0,0000070 | 0,0000056 | -0,0000365 | 0,0000107 | 0,0000109 | 0,0000902 | 0,0001777 | 0,0001576 | -0,0000275 | 0,0000123 | -0,0000054 |
| PETKM | -0,0000232 | 0,0000123 | -0,0000062 | 0,0000339 | -0,0000333 | 0,0000000 | -0,0000053 | -0,0000243 | 0,0000144 | 0,0000302 | -0,0000150 | -0,0000073 | -0,0001557 | -0,0000070 | **0,0003472** | 0,0000093 | -0,0000193 | -0,0000228 | 0,0000820 | -0,0000109 | -0,0000314 | -0,0000303 | -0,0000026 | -0,0000198 | 0,0000231 |
| TOASO | 0,0000058 | 0,0000025 | 0,0000061 | -0,0000065 | -0,0000139 | -0,0000448 | -0,0000079 | 0,0000178 | 0,0001094 | -0,0000045 | 0,0000014 | -0,0000070 | -0,0000771 | 0,0000056 | 0,0000093 | **0,0002540** | -0,0000013 | 0,0000102 | -0,0000013 | 0,0000122 | 0,0000022 | 0,0000110 | -0,0000378 | 0,0000057 | 0,0000166 |
| SODA | -0,0000192 | 0,0000043 | 0,0000174 | 0,0000034 | -0,0000273 | -0,0001021 | -0,0000194 | -0,0000215 | 0,0000123 | -0,0000064 | -0,0000270 | -0,0000068 | -0,0000232 | -0,0000365 | -0,0000193 | -0,0000013 | **0,0002361** | -0,0000168 | 0,0000139 | -0,0000066 | -0,0000199 | -0,0000225 | 0,0000256 | 0,0000016 | -0,0000029 |
| THYAO | 0,0000235 | 0,0000004 | -0,0000127 | -0,0000146 | -0,0000052 | 0,0001058 | -0,0000049 | 0,0000160 | -0,0000094 | -0,0000283 | 0,0000163 | 0,0003245 | 0,0007100 | 0,0000107 | -0,0000228 | 0,0000102 | -0,0000168 | **0,0005961** | 0,0000204 | 0,0000253 | 0,0000113 | 0,0000226 | 0,0000009 | 0,0000140 | 0,0000151 |
| TCELL | 0,0000152 | -0,0000120 | -0,0000070 | 0,0000606 | -0,0000194 | 0,0000323 | 0,0000087 | 0,0000145 | 0,0000053 | 0,0000186 | 0,0000045 | 0,0000112 | -0,0000622 | 0,0000109 | 0,0000820 | -0,0000013 | 0,0000139 | 0,0000204 | **0,0002535** | 0,0000064 | 0,0000200 | 0,0000079 | 0,0000194 | -0,0000225 | -0,0000049 |
| TUPRS | 0,0000827 | -0,0000031 | -0,0000150 | -0,0000038 | 0,0001046 | 0,0000730 | -0,0000153 | 0,0000939 | -0,0000138 | -0,0000200 | 0,0000672 | 0,0000103 | -0,0001218 | 0,0000902 | -0,0000109 | 0,0000122 | -0,0000066 | 0,0000253 | 0,0000064 | **0,0002787** | 0,0001021 | 0,0001036 | 0,0000061 | 0,0000022 | -0,0000146 |
| VAKBN | 0,0002733 | -0,0000105 | -0,0000101 | 0,0000366 | 0,0001913 | 0,0002468 | 0,0000214 | 0,0002903 | -0,0000291 | -0,0000173 | 0,0001683 | -0,0000249 | 0,0003190 | 0,0001777 | -0,0000314 | 0,0000022 | -0,0000199 | 0,0000113 | 0,0000200 | 0,0001021 | **0,0003974** | 0,0002919 | -0,0000207 | -0,0000019 | -0,0000048 |
| YKBNK | 0,0002566 | -0,0000250 | -0,0000050 | 0,0000219 | 0,0001973 | 0,0002561 | -0,0000012 | 0,0002733 | -0,0000098 | -0,0000219 | 0,0001764 | -0,0000244 | 0,0001626 | 0,0001576 | -0,0000303 | 0,0000110 | -0,0000225 | 0,0000226 | 0,0000079 | 0,0001036 | 0,0002919 | **0,0003736** | -0,0000263 | -0,0000049 | -0,0000113 |
| EREGL | -0,0000195 | 0,0000158 | -0,0000015 | -0,0000056 | -0,0000454 | -0,0000412 | -0,0000187 | -0,0000206 | 0,0000062 | 0,0000058 | -0,0000107 | 0,0000024 | -0,0003847 | -0,0000275 | -0,0000026 | -0,0000378 | 0,0000256 | 0,0000009 | 0,0000194 | 0,0000061 | -0,0000207 | -0,0000263 | **0,0004376** | 0,0000949 | -0,0000074 |
| TTKOM | -0,0000086 | -0,0000159 | -0,0000130 | -0,0000090 | -0,0000485 | 0,0000179 | -0,0000057 | -0,0000096 | 0,0000048 | 0,0000062 | -0,0000001 | -0,0000161 | 0,0000758 | 0,0000123 | -0,0000198 | 0,0000057 | 0,0000016 | 0,0000140 | -0,0000225 | 0,0000022 | -0,0000019 | -0,0000049 | 0,0000949 | **0,0004284** | -0,000275 |
| KCHOL | -0,0000119 | 0,0000396 | 0,0000079 | 0,0000030 | -0,0000471 | -0,0000603 | 0,0000226 | -0,0000212 | 0,0000158 | 0,0000109 | -0,000051 | 0,0000193 | -0,0000044 | -0,0000054 | 0,0000231 | 0,0000166 | -0,0000029 | 0,0000151 | -0,0000049 | -0,0000146 | -0,0000048 | -0,0000113 | -0,000074 | -0,000275 | **0,0002733** |

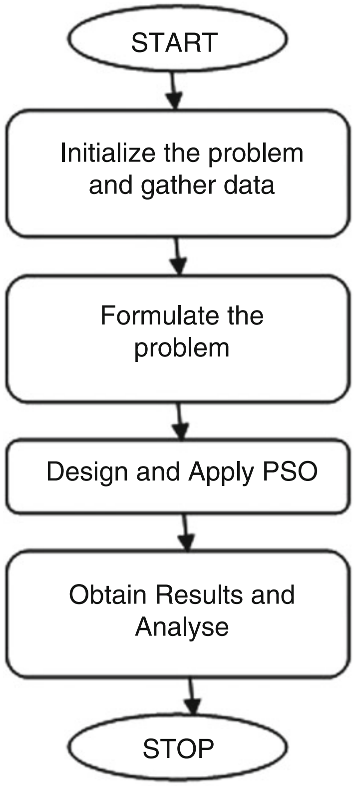


**Fig. 9.1** Implementation step flowchart of basic PSO. Source: Authors' own creation

the program to get perfect results. PSO is then executed to obtain results for the defined problem.

### *9.4.1 Problem Definition*

PSO is used to solve the optimization problem of portfolio optimization. The main component of the problem is the fitness function that is the Markowitz mean-variance model in this study. A separate function is defined for obtaining the fitness function of a random particle. MATLAB is used to implement PSO as well as the fitness function.

In the program, PSO uses the fitness function again and again to evaluate various particles. In the initial part of PSO, the particles are randomly generated within the search space. These particles represent a candidate solution, i.e., any particle can represent a full solution to the problem. The solution to the problem is a weight matrix of size $1 \times 25$, as the number of stocks is 25. In case the number of stocks is more or less, the matrix size of the weights will also change accordingly. One row

**Table 9.4** A particle in PSO

| | | | | |
|---|---|---|---|---|
| 0.040936 | 0.056778 | 0.055031 | 0.060798 | 0.022407 |
| 0.053885 | 0.043314 | 0.030853 | 0.004792 | 0.060705 |
| 0.026267 | 0.047298 | 0.057676 | 0.008155 | 0.009951 |
| 0.042759 | 0.037755 | 0.069287 | 0.062166 | 0.057138 |
| 0.003994 | 0.005671 | 0.006888 | 0.062119 | 0.073375 |

matrix of size $1 \times 25$ represents one particle. The members of the matrix should be in the range of 0–1 and should follow the constraint mentioned in Eq. (9.6).

Table 9.4 gives an example of a particle generated randomly at the start of the program. Due to the space constraint, the values are arranged in five rows, but in the code, it should be a single row matrix.

If all the values are added of Table 9.4, it is observed that the constraint of the problem is satisfied and the total comes out to be unity.

In the program, 30 particles are taken which are generated at the beginning of the program. This collection of 30 particles is called the **population**. Next it is needed to evaluate the fitness function of each variable.

The fitness function is separately defined as mentioned earlier. The algorithm for the same function is given below:

```
Algorithm for Fitness Function Evaluation
Get Required Data
Get the Particle to be evaluated
SumFF = 0;
for 1 to No of Stocks do
 for 1 to No of Stocks do
 SumFF = SumFF + Wi * Wj * Cov (Ri, Rj)
 end for
end for
Return SumFF
```

In the above algorithm, $W_i$ and $W_j$ are the weights at positions "i" and "j," respectively, in the particle. Also SumFF represents the **fitness function** value.

Once fitness function values are obtained for all the particles, it is proceeded to implement PSO. In PSO, all the particles move with a certain velocity to converge at the end to the global optimal solution. The movement of the particles is termed as its **velocity**. The velocity of a particle is dependent on inertia, the influence of its own best position, and the global best position.

In each iteration of PSO,

(i) Velocity for all the particles is calculated.
(ii) The individual positions of the particles are updated.
(iii) Fitness function is found for all the particles.
(iv) The individual and global best positions are updated.

The same is represented in the algorithm given below:

```
Algorithm for Particle Swarm Optimization
Input Required Data
Generate Random Particles
Evaluate the Fitness Function of these Particles
for 1 to Max Iterdo
 for 1 to Population Size do
 Calculate velocity
 Update Particle Position
 Obtain Fitness Function
 Update Individual Best
 endfor
 Update Global Best
endfor
```

### 9.4.2 Parameters of PSO

Some of the parameters that control PSO are described below:

Maximum Number of Iterations: PSO is an iteration-based optimization model. The PSO technique can be stopped through three different conditions, viz., (a) based on the number of iterations, (b) convergence, and (c) if the global best does not improve for a certain number of iterations. It is gone by the first condition and stops the PSO method at 200 iterations. A high number of iterations would lead to an extended solution time.

Population Size: Population size gives the number of particles used to search the optimal global best position. Usually 30–50 particles are utilized in a PSO method. In the case, it is created 30 particles to search the global best in the available search space.

Dimensions of the Search Space: The number of input variables defines the dimensions of these arch spaces. In portfolio optimization, the number of stocks shall define the number of dimensions of these arch spaces. Currently, as 25 stocks have been considered, the dimension of these arch spaces will be 25. In case the number of stocks changes, the dimensions of these arch spaces will also change.

Inertia Coefficient: Inertia coefficient is a very important parameter in these arch processes of PSO. A higher value of inertia coefficient represents more exploration and less exploitation, whereas a lesser value of inertia coefficient represents more exploitation and lesser exploration. Both exploration and exploitation should be properly matched for the optimal operation of PSO. Inertia coefficient is modified to constriction factor in Clerc (1999). The value of the constriction factor is fixed to 0.729 in the present case.

The other parameters of PSO are *c1*, individual acceleration coefficient, and *c2*, social or global acceleration coefficients which are taken as 2.05.

PSO is executed for 200 iterations with 30 particles for the case presented above. The variation in the global best position is presented in Fig. 9.2.

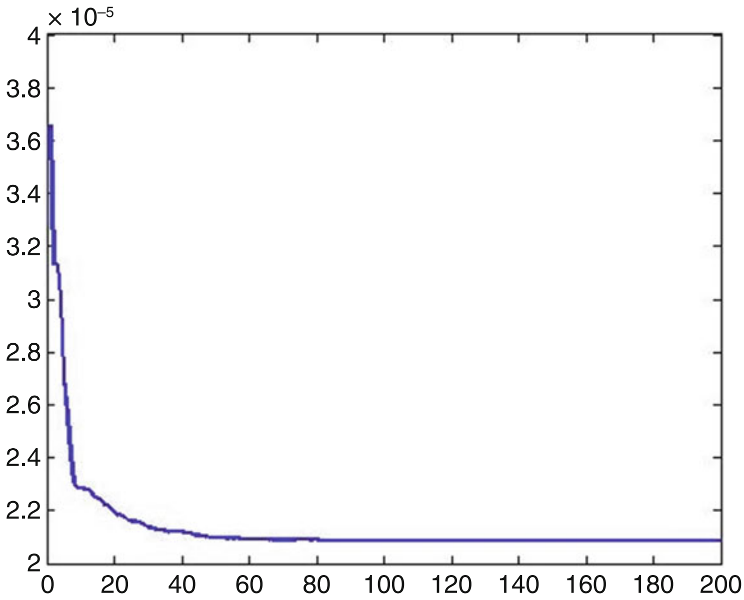


**Fig. 9.2** Change in objective function value concerning the number of iterations. Source: Authors' own creation

A comparison of the optimal solution found by PSO and nonlinear GRG methods is presented in Table 9.5.

Portfolio return is estimated based on the weights which minimize the risk level. According to the PSO and nonlinear GRG techniques, the optimal portfolio return, variance, and standard deviation are calculated and shown in Table 9.6.

In Table 9.7, the results obtained by using PSO and nonlinear GRG techniques give close values. However, the coefficients of variation are calculated here to see which method gives better results.

It has similar results and PSO can thus be used as an alternative. Since quite similar results are obtained from two different techniques, it also proves the reliability of the techniques.

## 9.5 Conclusion

Optimization is the process of getting the best solution while conducting specific operations for a specific purpose. Portfolio selection problem depends on investors' expectations and model's constraints. According to the investors' certain expectations and model's certain constraints, the decision is made to create an optimum portfolio from a variety of assets. Regarding the correlation coefficients of the asset returns, while adding new assets to a risky portfolio, the total risk decreases.

**Table 9.5** Weights of the 25 stocks in the optimal portfolio by using PSO and nonlinear GRG techniques

| | Weights PSO | Weights Nonlinear GRG |
|---|---|---|
| AKBNK | 0.00000000 | 0.00000000 |
| ARCLK | 0.07329542 | 0.07304953 |
| ASELS | 0.02131277 | 0.02123730 |
| BIMAS | 0.08607284 | 0.08620884 |
| DOHOL | 0.01410830 | 0.01435069 |
| KOZAA | 0.01253312 | 0.01272358 |
| HALKB | 0.04394518 | 0.04404135 |
| GARAN | 0.00000000 | 0.00000000 |
| ISCTR | 0.04603436 | 0.04640693 |
| SISE | 0.10035837 | 0.10070752 |
| SAHOL | 0.07655238 | 0.07521591 |
| KRDMD | 0.02236350 | 0.02222367 |
| TKFEN | 0.00052400 | 0.00052697 |
| TAVHL | 0.02135613 | 0.02159467 |
| PETKM | 0.04458688 | 0.04490066 |
| TOASO | 0.06552657 | 0.06545679 |
| SODA | 0.10943198 | 0.10966535 |
| THYAO | 0.02348696 | 0.02350349 |
| TCELL | 0.03149002 | 0.03098662 |
| TUPRS | 0.05588755 | 0.05625737 |
| VAKBN | 0.00000000 | 0.00000000 |
| YKBNK | 0.00000000 | 0.00001677 |
| EREGL | 0.03970906 | 0.03976780 |
| TTKOM | 0.05026441 | 0.05014628 |
| KCHOL | 0.06116019 | 0.06101188 |
| Sum | 1.00000000 | 1.00000000 |

**Table 9.6** Optimal portfolio return, variance, and standard deviation

| | Optimal portfolio PSO | Optimal portfolio Nonlinear GRG |
|---|---|---|
| Portfolio return | 0.0006485847 | 0.0006514079 |
| Portfolio var | 0.0000208684 | 0.0000208690 |
| Portfolio std dev | 0.0045681989 | 0.0045682613 |

Obtained from PSO and nonlinear GRG techniques

**Table 9.7** Coefficient of variation of optimum portfolios

| | PSO | Nonlinear GRG |
|---|---|---|
| Coefficient of variation (standard dev./return) | 7.043334356 | 7.01290436 |

According to the Markowitz portfolio theory, if the correlation coefficients of two asset returns are less than 1, the total risk of that portfolio constantly decreases (Markowitz, 1952). Indeed, if the correlation coefficient is negative, the total risk of the portfolio can be decreased much more. However, it is an exceedingly difficult situation to be a negative correlation coefficient of two assets in real life. PSO is one of the techniques that can be used to determine the optimum portfolio. The technique depends on animals' environment. PSO used the ability of animals such as birds and fish to adapt to their environment by applying a "knowledge-sharing" approach, finding rich food sources, and avoiding predators. This chapter deals with portfolio selection problem and tries to indicate how to select financial assets to conduct optimal portfolio between BIST-30 index stocks by using the particle swarm optimization (PSO) technique, which is the heuristic algorithm. In addition, to compare the results, the optimization problem is solved by nonlinear GRG techniques. Then, the results of both techniques are compared.

The data set analyzed in the chapter is organized from simultaneous stocks of BIST-30 index for the period of June 2016–July 2018. The problem is coded with MATLAB to evaluate the optimal portfolio algorithm that requires a solution. By using these returns, the optimum portfolio with minimum risk is created with PSO and nonlinear GRG techniques.

The results obtained show that both methods give similar results. The results obtained by both using PSO and nonlinear GRG techniques give close values. The coefficients of variation are remarkably close. Since quite similar results are obtained from two different techniques, it also proves the reliability of the techniques. The application of PSO in solving optimization problems could be the very facilitator in real financial life.

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