Portfolio Management by using Value at Risk (VaR) (A Comparison between Particle Swarm Optimization and Genetic Algorithms)

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Abstract: This paper aims at comparing particle swarm optimization (PSO) with genetic algorithm (GA) for portfolio management in a constrained portfolio optimization problem in which short selling is not permitted. The minimized objective function is value-at-risk calculated by using historical simulation. The tests results reveal that these methods are able to calculate consistently the optimized solutions within a proper time. With respect to the statistical calculations, it is concluded that these algorithms do not lead to a best solution identically. In terms of time of implementation and number of iterations, particle swarm optimization seems to reach more swiftly to the solution compared with genetic algorithm; and in terms of sensitivity to the initial position of the particles, particle swarm optimization is more leading than genetic algorithm. Among other findings of this paper is that 50 particles (chromosomes) are sufficient for problems with up to 20 assets.
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Introduction

Portfolio refers to a set of assets invested by an investor. A portfolio embraces technically a complete set of real and financial assets. Financial assets include different types of securities like bonds, ordinary stocks, preferred stocks, and financial derivatives (DiTraglia, F.J. and et al., 2013). Portfolio management is the most important matter for a portfolio. Portfolio management constitutes the major part and focal point of investment management concept. Portfolio management embraces all dimensions of the portfolio and it includes combination of stocks existing in the portfolio, weight of each stock in the portfolio, and the best time for changing the combination. On the other hand, the most important part of portfolio management is portfolio optimization which refers to the selection of the best combination of financial assets so as to maximize return on investment portfolio and minimize portfolio risk as much as possible. In fact in portfolio optimization, selection of the optimized assets and securities with a certain amount of capital is the main matter. It must be noted that a portfolio that includes several assets (Portfolio diversification) reduces risk in general (risk of an asset refers to a probable change in its future return) (Reboredo, J.C., 2013).

There are different methods for optimization in general and portfolio optimization in particular. Many studies have been carried out in the recent years regarding development of portfolio optimization methods based on new theories including value at risk theory. This paper seeks to design an optimal portfolio which minimizes value at risk calculated by historical simulation based on intelligent optimization methods and with regard to the constraints on the weights of the assets in the portfolio. Intelligent optimization methods are very more quick and reliable compared with older methods (Huang, W., et al., 2012). One of the main issues raised in the capital market is selection of an optimal portfolio (with a minimum risk).

The objective of the present paper is managing portfolio by using value at risk and comparing genetic algorithm with particle swarm optimization. The results obtained by this paper may be used by all natural and legal investors to improve portfolio selection and reduce risks.

2. Literature Review

Here, a summary of several financial definitions and prerequisites used in this paper and then studies carried out in this regard are presented.

2.1 Theoretical Concepts

Asset: anything that produces profit is called asset. In the economy, assets are divided into two groups namely, financial assets (their physical aspect does not have value and they are regarded among securities) and real assets (their physical aspect has value and they are tangible) (Alexander, G.J. et al., 2011).

Financial market: any network in which goods and services are traded. The market does not have a physical concept and does not occupy a specific space necessarily (Das, S. et al., 2010).

Stock Exchange: an official capital market in which stocks of companies or bonds of government or reliable private institutions are traded as per specific rules and regulations (Chonghui, J. et al., 2013).

Stock: a part of the assets of a company or a factory. The stockholder is a partner in the ownership of a manufacturing firm or company to the extent of the held stocks (Jiang, C., et al., 2010).

Investment: passing up consumption in the present to hope to consume more in the future (Baptista, A. M., 2012).

Portfolio: a combination of assets constituted for investments by an investor (Alexander, G. J. et al., 2010).

Return on assets: taking benefit from an asset; this paper applies three types of returns.

Simple periodic return => $R_t = (P_t - P_{t-1}) / P_{t-1}$, where P_t denotes the price of asset at t time.

Continuously compounded return => $r_t = \ln(1 + R_t)$, where r_t denotes natural logarithm of simple return.

Portfolio return => $R_{\sqcap, t} = \Sigma \omega_i R_{i,t}$ (i = 1, … n) , where ⊓denotes portfolio, N is type of asset, i represents weight of the related asset in the portfolio ω_i, and ω_i is a percentage of portfolio value due to the i-th asset (Mansoorian, A., et al., 2013).

Actualized return => a return that has been actualized or obtained (Durham, G., et al., 2012).

Expected return => an estimated return of an asset that investors expect to obtain in the future (GHATTASSI, I., 2013).

Risk: the measurable potential loss is called risk in which two variables namely loss and uncertainty are involved (Bonato, M., et al., 2012).

Value at risk (VaR): X percent confidence (1- α) in preserving currency V (value) in N (time) days. The advantages of this method include its applicability to stocks, bonds, goods, etc., applicability to financial instruments whose return distribution is normal or abnormal, being a framework for risk measurement and analysis, preventing lateral calculations, and having a leading approach towards risk measurement (Holton, G. A., 2003).

Conditional value at risk (CVaR): loss prediction under unfavorable conditions. At confidence level 1 - α, it equals $CVaR_{(1-\alpha)} = -E[X \mid X \leq -VaR_{(1-\alpha)}]$, where X denotes real-valued random variable, $f\text{x}(x)$ is the probability density function and $X_\alpha = VaR_{(1-\alpha)}$ (Inui, K., et al., 2005).

Genetic algorithm: it is based on Darwin's evolutionary theory and the solutions of problems solved through genetic algorithm improve gradually. This algorithm starts from a set of solutions (chromosomes / population). In this method, solutions obtained from one population are used for producing next population. Selection of some solutions (parents) for creating new solutions (off springs) is based on fitness value (Blanco, A., et al., 2001).

PSO algorithm: it presents a set of solutions (with learning feature) which is called particle (like chromosome). In portfolio, total weights of assets constitute a particle. Each particle in PSO has a position in the search space. The position of each particle is determined based on the experience of the particle and its neighbors. In each PSO, two simple behaviors are modeled namely, movement of each particle towards the best and nearest neighbor, and return of each particle to a state that has been better for it earlier (Mirzaei, et al., 2011).

2.2 Research Background

The studies related to the subject of this paper are presented in the following.

(Goovaerts, M. and et. al, 2012), in the actuarial research, distortion, mean value and Haezendonck–Goovaerts risk measures are concepts that are usually treated separately. (Ruodu, W. et. al, 2013), provide a new lower bound for any given marginal distributions and give a necessary and sufficient condition for the sharpness of this new bound. For the sum of dependent risks with an identical distribution, which has either a monotone density or a tail-monotone density, the explicit values of the worst Value-at-Risk and bounds on the distribution of the total risk are obtained. (Bianconi, M. et. al, 2013), We analyze a sample of 64 oil and gas companies of the nonrenewable energy sector from 26 countries using daily observations on return on stock from July 15, 2003 to August 14, 2012. A panel model with fixed effects and Tarch effects shows significant prices for specific risk factors including company size and debt-to-equity and significant prices for common risk factors including the U.S. Dow Jones market excess return, the Vix, the WTI price of crude oil, and the FX of the euro, Chinese yuan, Brazilian real, Japanese yen, and British pound vis-a-vis the U.S. dollar. (Burchi, A., 2013), This paper aims to investigate the effects of different models to estimate the market risk in the management of the trading book. The study takes into account the events occurring in the financial markets and the new prudential rules. Design/methodology/approach – The author compares different models and proposes an opportunity cost function able to evaluate the cost related to capital requirements. This paper presents several state of the art methods to evaluate the adequacy of almost any given market risk model. Existing models are enhanced by in-depth analysis and simulations of statistical properties revealing some previously unknown effects, most notably inconsistent behavior of alpha and beta errors. Furthermore, some new market risk validation models are introduced. This paper examines the relation between bank charter value and risk taking. Using a sample of U.S. banks over the period 1990–2006, we find that the relation is U-shaped: as charter value increases, risk taking first decreases and then increases. This finding is robust across alternative measures of risk taking and an estimation method that accounts for the joint determination of charter value and risk taking. (Zapodeanu, D. et. al, 2012), In the Value at Risk methodology the estimation models are classified as: parametric, nonparametric, semi-parametric; they present the parametric models (GARCH models) used in Value at Risk and the connections that can be established between ALM models and Value at Risk. We present the Conditional Value-at-risk and offer and example on how to calculate CVaR. (So, M. et. al, 2013), In this paper, we develop modeling tools to forecast Value-at-Risk and volatility with investment horizons of less than one day. We quantify the market risk based on the study at a 30-min time horizon using modified GARCH models. The evaluation of intraday market risk can be useful to market participants (day traders and market makers) involved in frequent trading. As expected, the volatility features a significant intraday seasonality, which motivates us to include the intraday seasonal indexes in the GARCH models.

3. Research Methodology

For the empirical part of this paper, data pertaining to active market of Stock Exchange in America for 30 stocks (companies) from 5 January 1987 to 30 May 2006 has been used. In sum, 4896 data points were obtained. Using above data, computational model of the return logarithm was determined as $r_{t,k} = \log (p_{t.k} / p_{(t-1),k})$. As per the research literature, objective function N is variable and its mathematical model equals,

$\min_{\omega 1 \dots \omega n}$ (VaR),

s.t.

$\Sigma\omega_i = 1$ (i = 1 ... n)

$\forall i : 0 \leq \omega_i \leq 1$

The main objective of this paper is solving the problem by two PSO and GA algorithms and comparing their functions in reaching the solution. So the problem assumptions are as per below.

a. Initial value of particles / chromosomes in algorithms

Chromosomes and particles must be initially valued, because the optimal zone in the probable space is not known in advance. To implement valuing process, below steps are passed through.

- ✓ Creating the vector $\vec{S} = [1, 2, \dots N]$, where N is the number of assets in the problem.
- ✓ Creating a random permutation of vectors $\vec{S'}$ and $\vec{S'}$
- ✓ Producing sequence weights determined by $\vec{S'}$
- ✓ Normalizing weights determined for maximizing up to one

b. Size of algorithms population in the model

In PSO algorithm, size of population refers to the number of particles. The more the number of particles in the population is, the more the initial divergence of the population will be. As the population gets larger, in each round of PSO algorithm ring, more search space is covered and computational sophistication is also increased and searches are converted into parallel random search. Compared with low particles, as the number of particles gets more, we will reach solution in fewer rings. In this paper 30 particles are not sufficient. Thus for most experiments carried out here, population size has been selected 50.

c. Algorithms parameters in the model

To use the related algorithms for solving the optimization problem, it is necessary to specify their parameters experimentally. Thus below values have been selected for PSO.

$\omega_{max} = 0.9$ $\omega_{min} = 0.4$

$C_1 = 0.5$ $C_2 = 0.5$

$p_1 = 0.9$ $P_2 = 0.9$

Genetic algorithm has two parameters as below.

- ✓ Calculating probability of a combination in two selected chromosomes
- ✓ Calculating probability of a mutation in the offspring (two solutions)

Occurrence probability of a combination is assumed 0.8 (or 80%) and probability of a mutation is assumed 0.01 (or 1%). Confidence level for VaR and CVaR has been considered 95%. Tests of this paper cover two goals namely, ability of finding the optimal solution and speed of convergence. To realize ability of finding optimal solution, below parameters have been considered.

- ✓ The average number of iterations required for an algorithm ($\overline{N}_{it}$)
- ✓ Standard deviation of the number of iterations (σ_N)

- ✓ The mean error between the best solution found by an algorithm in each implementation and the best solution found in all implementations ($\bar{\varepsilon}_{VaR}$)
- ✓ Standard deviation of error $\bar{\varepsilon}_{VaR}$ (σ_{ε})

Two late items depict that how much the algorithm is proper for finding the optimal solution in the problem. To investigate convergence speed, each algorithm has been considered 5 times for each of the 5 sub sets (random selection), implementation and average of time of each iteration are calculated. Parameters are defined as per below.

- ✓ Time of each iteration (t/it)
- ✓ Average time of each iteration $(\overline{t/it})$
- ✓ Average time required for convergence of each algorithm $(\bar{t})$

To know how long it does take for an algorithm to converge, below assumptions are regarded.

- – If the algorithm is iterated $N'_{it} = \bar{N}_{it} + 2\sigma_N$ times, by 0.1% approximation it reaches the best solution found in 97.7% times of a specific implementation.
- – The main assumption is that $\bar{N}_{it}$ has an approximate normal distribution. The test has been carried out via matlab 7. The codes applied in the software have been mentioned in the appendix.

4. Research Findings

4.1 Risk Values

To show the effect of selecting different horizons for inputs, portfolios with 5 assets (stocks of M3, Citigroup, Coca Cola, General Motors, and Microsoft) have been optimized for different risks size. Sizes of risks are namely variance, VaR calculated by historical simulation, and CVaR calculated by historical simulation. Figure 1 to 3 and table 1 presents weights of optimal portfolio by using different objective functions and different time horizons for data. In the figures, Y-axis shows the weights and X-axis shows the time (year).

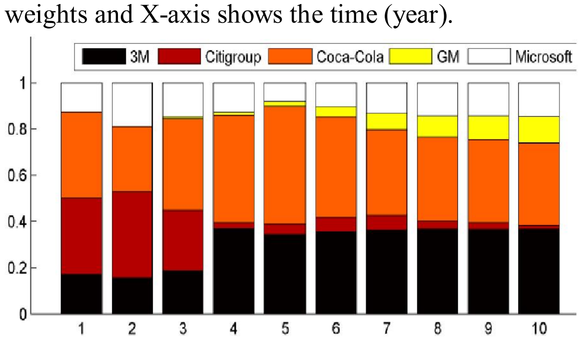

Figure 1. Minimization of variance of portfolio returns

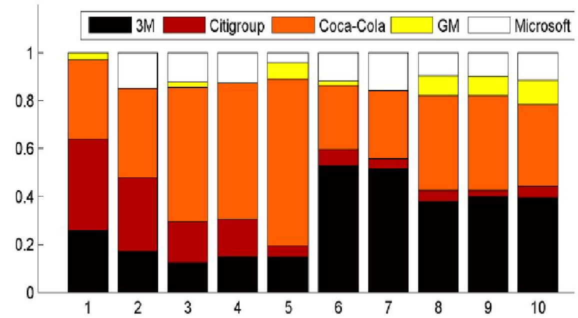

Figure 2. Minimization of VaR of portfolio returns

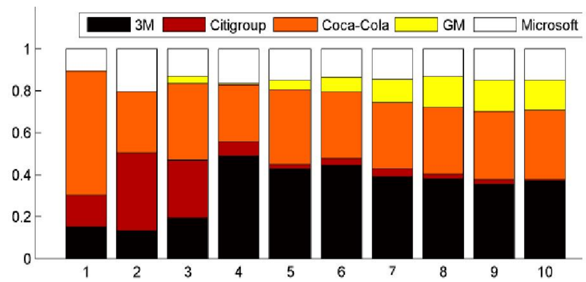

Figure 3. Minimization of CVaR of portfolio returns

With regard to the size of applied risk, combination of a portfolio may vary highly. For example, this situation can be seen as regards Coca Cola stocks in the portfolio generated by data of 5 years (a five-year horizon). By this horizon, the weight of Coca Cola stocks equals 50.1% in a portfolio that minimizes the variance, equals 69.7% by VaR minimization and 35.6% by CVaR minimization.

Table 1. Variance, VaR, and CVaR minimization of portfolio returns

Minimization	Variance	VaR	CVaR
Variance	-	%5.56	%0.12
VaR	%0.77	-	%0.49
CVaR	%0.09	%5.09	-

Different risks size of portfolios with 5 identical assets that are optimized by VaR, CVaR, and variance minimization are compared. Then these portfolios are measured by different metrics. Minimization reveals that the objective function has been minimized. Variance, VaR, and CVaR shows standard deviation of a portfolio that has minimized these criteria.

4.2 Ability to Find the Optimal Solution

Ability to generate the optimal solution by these algorithms to optimize the problem with 50 particles / chromosomes and with portfolio including 5, 10, and 20 sub sets was tested and the results are presented in table 2. With regard to the executive model of the research, strategies that have been used in calculations are namely PSO (Bumping, Amnesia, Random, Penalty) and GA (Roul./Basic, Tourn./Basic, Roul./Arith, Tourn./Arith) , and genetic algorithm has been calculated for 5-item sub sets.

Table 2. Minimization of variance, VaR, and CVaR of portfolio returns

N_α	Algorithm	$\overline{N}_\alpha$	σ_N	$\overline{\varepsilon}_{VaR}$	σ_ε
5	PSO Bumping	44	21	% 0.58	% 0.79
	PSO Amnesia	79.7	31	% 0.55	% 0.73
	PSO Random	562.7	522.6	% 0.37	% 0.6
	PSO Penalty	93.8	54.1	% 0.37	% 0.69
	GA Roul./Basic	142	168.7	% 0.52	% 0.72
	GA Tourn./Basic	172.6	242.1	% 0.6	% 0.78
	GA Roul./Arith	472.6	574.2	% 0.91	% 1.06
	GA Tourn./Arith	269.1	415	% 1.02	% 1.02
10	PSO Bumping	102.1	53.3	% 3.43	% 1.38
	PSO Amnesia	163.4	103.8	% 4.02	% 2.30
	PSO Random	1473.3	427.5	% 2.29	% 1.41
	PSO Penalty	190.4	88.1	% 3.34	% 2.49
	GA Roul./Basic	793	518.1	% 2.65	% 1.76
	GA Tourn./Basic	680	507.2	% 3.37	% 1.79
	GA Roul./Arith	1257	454.5	% 3.12	% 1.96
	GA Tourn./Arith	808.8	550.8	% 3.66	% 1.76
20	PSO Bumping	119.1	52.1	% 5.27	% 2.5
	PSO Amnesia	320.6	96.8	% 6.77	% 2.31
	PSO Random	1798.8	272.7	% 4.99	% 2.4
	PSO Penalty	299.6	65.4	% 6.29	% 3.26
	GA Roul./Basic	1239.6	506.4	% 3.62	% 2.24
	GA Tourn./Basic	1078.4	510.8	% 3.46	% 2.28
	GA Roul./Arith	1615.2	272.6	% 5.72	% 2.05
	GA Tourn./Arith	1298.2	365.8	% 4.6	% 2.78

Table 3. Comparison of speed of PSO and GA algorithms

N_α	Algorithm	$\overline{t / it}(ms)$	N'_{it}	$\overline{t}(s)$
5	PSO Bumping	34.2	86	2.9
	PSO Amnesia	33.9	142	4.8
	PSO Random	33.9	1608	54.5
	PSO Penalty	34.5	202	7
	GA Roul./Basic	44.2	479	21.2
	GA Tourn./Basic	43.7	657	28.7
	GA Roul./Arith	43	1621	69.7
	GA Tourn./Arith	42.6	1099	46.8
10	PSO Bumping	46.5	2.9	9.7
	PSO Amnesia	46	371	17.1
	PSO Random	46	2328	107.1
	PSO Penalty	46.6	367	17.1
	GA Roul./Basic	69.6	1829	127.3
	GA Tourn./Basic	69.2	1695	117.2
	GA Roul./Arith	68.3	2166	148
	GA Tourn./Arith	68	1910	129.9
20	PSO Bumping	70.8	223	15.8
	PSO Amnesia	70.1	514	36
	PSO Random	70.5	2344	165.1
	PSO Penalty	71.2	430	30.6
	GA Roul./Basic	121.6	2253	274.1
	GA Tourn./Basic	121.3	2100	254.6
	GA Roul./Arith	120	2160	259.3
	GA Tourn./Arith	120.1	2030	243.7

Analysis of GA function in table 2 depicts that when we talk about number of iterations required for convergence, its function is worse than PSO process. The reason of this situation is that PSO is a more focused search process, while GA is a more random display. This random state in GA identifies a wider search space and this feature creates some solutions closer to the optimal value ($\overline{\varepsilon_{VaR}}$) for problems with more dimensions (optimization of portfolio with 20 assets). This fact reveals that GA is apparently less likely to converge to a local minimum compared with PSO; albeit, it excludes random positioning strategy. However, the function of random positioning strategy for PSO (particularly for more assets) seems worse than function of GA.

4.3 Speed of Convergence

The second test of this paper is measurement of the algorithm speed carried out by 50 particles / chromosomes and a portfolio including 5, 10, and 20 sub sets. In this test, $\bar{t}$ denotes the average time (sec) and $\overline{t / it}$ is the average time of an iteration of the algorithm. Table 3 presents the results.

As shown, for any size of portfolio, PSO has used less time for calculations in any iteration compared with GA. For portfolios with 5 assets, GA requires about 30% more time than PSO for any iteration. For portfolios with 10 assets, 45% more time, and for portfolios with 20 assets, 70% more time is required.

5. Conclusion and Suggestions

This paper demonstrated application of particles swarm optimization and genetic algorithms for portfolio management in a constraint portfolio optimization problem. The minimized objective function was the value at risk calculated by historical simulation. The results revealed that particle swarm optimization and genetic methods can significantly find proper solutions within a reasonable time. The particle swarm optimization algorithm was proved to be quicker than genetic algorithm in terms of both total time of implementation and number of iterations. This is justifiable by its more focused search.

With respect to the strategies applied for particle swarm optimization algorithm, bumping strategy is the best one in terms of speed, and then the results of amnesia and penalty strategies are closed to it.

Genetic algorithm, like particle swarm optimization algorithm, was proved to be able to find a good solution, yet it showed a worse state in terms of speed. Its less focused search (more non-random state) makes it less engaged in the local minimum; particularly if the population is not initially valued by chromosomes distributed in a probable space. The results of optimization by genetic algorithm reflected that basic crossover is better than arithmetic crossover for exploring the solution space. Also GA. Roulette/arithmetic strategy is to some extent better than other methods. On the other hand, GA. tournament/Basic strategy is the worst one.

Suggestions

For further research as regards behavior of population-based algorithms, it is suggested,

- To assess the algorithms efficiency by considering some criteria for algorithms convergence.
- To investigate more consistency for portfolio management when encountering different time horizons (or different constraints) by PSO or GA algorithms.
- To compare consistency and speed of PSO and GA algorithms with each other in non-linear conditions.

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Appendix

Encoding VaR (objective function) by using historical simulation calculated in matlab.

```
%% Object function
function VaR=objectfunction(w)%w bordare vazn
load dadeha.txt;
[t,N]=size(dadeha);
r=zeros(t-1,N);

 for j=1:N
   for i=2:t
        r(i-1,j)=log(dadeha(i,j)/dadeha(i-1,j));
   end
 end
 for i=1:t-1
   for j=1:N
       E(i,j)=exp(r(i,j));
   end
end
 for j=1:N
           wt(:,j)=w(j).*E(:,j);
 end
 for i=1:t-1
        R(i)=log(sum(wt(i,:)));
 end
 ee=zeros(1,t-1);
 ee(5)=1;
 VaR=-ee*(sort(R))';
 end
```

Codes related to the genetic algorithm

```
function var_ga
s=input('s==1=Roulette selection ,s==2=tournament selection');
d=input('d==1=crossover Basic,d==2=crossover arithmetic');
q=input('inter q: q bar 5 adade tasadofi tolid mishavad:');

p=input('inter p:matrishaye entekhabi bar asase adade tasadofi p bar ejra mishavand:');
maxit=input('inter tedade tekrar')
c=.99;
n=zeros(1,p);
nn=zeros(1,q);
VR=zeros(1,p);
TT= zeros(1,q);
nn=zeros(1,q);
VRR=zeros(1,p);
vv=zeros(1,q);
Evar=zeros(1,q);
v=zeros(1,p);
for k=1:q
    i=1;
while i~=5
r=unique(randi(10,5,1));
[i,j]=size(r);
end
load dadeha.txt%iek matrise 500 * 10(matrise dadehaie asli ia avalie)
data=[dadeha(:,r(1)) dadeha(:,r(2))  dadeha(:,r(3)) dadeha(:,r(4)) dadeha(:,r(5))];
[t,N]=size(dadeha);

 for j=1:N
   for i=2:t
        r(i-1,j)=log(dadeha(i,j)/dadeha(i-1,j));
   end
 end
 for i=1:t-1
   for j=1:N
       E(i,j)=exp(r(i,j));
   end
 end
global E;
global N;
global t;
global c;
 for i=1:p
 options = gaoptimset('fitnesslimit',-inf);
if s==1
options = gaoptimset(options,'SelectionFcn',@selectionroulette);
% Roulette selection
end
if d==1
```

```
options=gaoptimset(options,'CrossoverFcn',@crossoversinglepoint);
%crossoversinglepoint is crossover Basic
end
options = gaoptimset(options,'SelectionFcn',{@selectiontournament,2});
%Tournament selection chooses each parent by choosing Tournament size
%players at random and then choosing the best individual out of that set
%to be a parent. Tournament size must be at least 2.
lb = zeros(N,1);


ub = ones(N,1);

%jahesh ba ravesh jahesh ba taghieer meghdar
options = gaoptimset(options,'CrossoverFraction',0.6);%The fraction of the
options=gaoptimset(options,'TolFun',1e-50);
%population at the next generation, not including elite children, that is
%created by the crossover function
options = gaoptimset(options,'Generations',maxit);%iek sharte tavaghof
options = gaoptimset(options,'MigrationFraction',.2);
options = gaoptimset(options,'PopulationSiz',50);%Population size (PopulationSize)
%specifies how many individuals there are in each generation.%andazeie jamiat dar har nasl
    brabare 50 ast.
options = gaoptimset(options,'PlotFcns',{@gaplotbestf,@gaplotbestindiv,@gaplotscores,
    @gaplotdistance,@gaplotrange,@gaplotselection},'Display','iter');
aeq=ones(1,N);
beq=1;
[w,VaR,exitflag,output,population,scores,] = ga(@objectfunction,N,[],[],aeq,beq,lb,ub,[],
    options);
stream = RandStream.getDefaultStream;
stream.State = output.rngstate.state;
 options = gaoptimset(options,'fitnesslimit',VaR+.01);
tic;
[w,VaR2,exitflag,output,population,scores] = ga(@objectfunction,N,[],[],aeq,beq,lb,ub,[],
    options);
T=toc;
NN=output.generations+100;
n(i)=NN
VR(i)=VaR2;
 end
TT(k)=sum(T)/p;
nn(k)=sum(n)/p
h=nn(k);
  for i=1:p
    v(i)=sqrt(((n(i)-h)^2)/p);
    VRR(i)=sqrt(((VR(i)-max(VR))^2)/p);
  end
Evar(k)=sum(VRR)/p;
end
avarageEvar=sum(Evar)/q
avarageT=sum(TT)/q
avaragen=sum(nn)/q
avaragevariance=sum(v)/q

function z=objectfunction(w)
global E;
global N;
global t;
global c;
 for j=1:N
            wt(:,j)=w(j).*E(:,j);
 end
 for i=1:t-1

        R(i)=log(sum(wt(i,:)));
 End

 ee=zeros(1,t-1);
 ee(5)=1;
 z=-ee*(sort(R))';
```

Codes related to the birds algorithm

```
function var_pso
MaxGeneration=input('tedade tekrar');
q=input('inter q: q bar 5 adade tasadofi tolid mishavad:');
p=input('inter p:matrishaye entekhabi bar asase adade tasadofi p bar ejra mishavand:');
maxit=MaxGeneration;
for k=1:q
    i=1;
while i~=5
r=unique(randi(10,5,1));
[i,j]=size(r);
end
load dadeha.txt%iek matrise 500 * 10(matrise dadehaie asli ia avalie)
data=[dadeha(:,r(1)) dadeha(:,r(2))  dadeha(:,r(3)) dadeha(:,r(4)) dadeha(:,r(5))];
[t,N]=size(data);
r=zeros(t-1,N);

 for j=1:N
   for i=2:t
         r(i-1,j)=log(data(i,j)/data(i-1,j));
   end
 end
 for i=1:t-1
   for j=1:N
       E(i,j)=exp(r(i,j));
   end
 end
 Vrr=zeros(1,p);
VRR=zeros(1,p);

 global E;
global N;
global t;
global c;
npop=50;%population size
nvar=10;%nomber of variable
wmax=.5;%parametrhaie dade shode dar safeie 775 maghaleie latin
wmin=.4%parametrhaie dade shode dar safeie 775 maghaleie latin
c1=.5;%zaribe afzaieshe sorat
c2=.5;%zaribe afzaieshe sorat

xmin=0;%[xmin,xmax]damaneie javabe behine
xmax=1;

vmax=.1;%maximom sorate mojaz braie zarat,safeie 16,17 pso;

empty_particle.position=[];
empty_particle.velocity=[];
empty_particle.objectfunction=[];
empty_particle.pbest=[];
empty_particle.pbestobjectfunction=[];

particle=repmat(empty_particle,npop,1);%tolide 50 zare ke har zare az 3 bordare mohgeiat
     zare,sorate zare,behtarin mogheiate zare tashkil shode.

gbest=zeros(maxit,nvar);%matrise behtarin mogheiate tamame zarat dar tamame tekrarha va dar
      hameie abad.
gbestobjectfunction=zeros(maxit,1);
for ii=1:p
     tic
for it=1:maxit
     if it==1
         gbestobjectfunction(1)=inf;%meghdare tabehadaf avalie be ezaie gbest
         for i=1:npop
              particle(i).velocity=zeros(1,nvar);%bordare sorate zareie iom
              particle(i).position=xmin+(xmax-xmin)*rand(1,nvar);%mohasebeie mogheiate zareie
                    iom
              particle(i).objectfunction=objectfunction(particle(i).position/sum(particle(i).
                  position)); % meghdare tabehadaf be ezaie mogheiate zareie iom iani:f(
                  particle(i).position)

```

```
            particle(i).pbest=particle(i).position;%mohasebeie behtarin mogheiate zareie iom ta tekrare t om
particle(i).pbestobjectfunction=particle(i).objectfunction;%meghdare tabhadaf be ezaie pbest iani:f(particle(i).pbest)

            if particle(i).pbestobjectfunction<gbestobjectfunction(it)
                gbest(it,:)=particle(i).pbest;
                gbestobjectfunction(it)=particle(i).pbestobjectfunction;
            end
        end
    else
        gbest(it,:)=gbest(it-1,:);
        gbestobjectfunction(it)=gbestobjectfunction(it-1);
        for i=1:npop%mohasebeie sorat, mogheiat,behtarin mogheiat zarat dar tekrare jadid
            particle(i).velocity=w*particle(i).velocity...
                                  +c1*rand*(particle(i).pbest-particle(i).position)...
                                  +c2*rand*(gbest(it,:)-particle(i).position);

            particle(i).velocity=min(max(particle(i).velocity,-vmax),vmax);%baraie kontorole sorat ke zare az fazaie mohtamel kharej nashavad.

            particle(i).position=particle(i).position+particle(i).velocity;%mohasebeie particle(i).position jadid

            particle(i).position=min(max(particle(i).position,xmin),xmax);

            particle(i).objectfunction=objectfunction(particle(i).position/sum(particle(i).position));

            if particle(i).objectfunction<particle(i).pbestobjectfunction
                particle(i).pbest=particle(i).position;
                particle(i).pbestobjectfunction=particle(i).objectfunction;

                if particle(i).pbestobjectfunction<gbestobjectfunction(it)
                    gbest(it,:)=particle(i).pbest;
                    gbestobjectfunction(it)=particle(i).pbestobjectfunction;
                end
            end
        end


    end

   % w=w*(it/maxit);% kahesh w be sorate khati ba zaribe kaheshi wdamp
   w=wmax-((wmax-wmin)*it)/maxit;%w zaribe ener30;;;; safeie 773 maghaleie latine asli
end
T(i)=toc;
for j=1:maxit
WS(j,:)=gbest(j,:)/(sum(gbest(j,:)));
vr(j)=objectfunction(WS(j,:))
end
IT=1;
for jj=1:maxit
    if (vr(maxit)+.01)>(vr(jj))
        IT=jj ;
        break
    end
end
n(ii)=IT; %tedade tekrar baraye residan b bazeye %1 javab behine
vrr(ii)=vr(maxit);
end
TT(k)=sum(T)/p; %miangine zamane residan b bazeye %1 javab behine dar p tekrar
nn(k)=sum(n)/p; %miangine tedade tekrar baraye residan b bazeye %1 javab behine dar p tekrar
h=nn(k);

  for i=1:p
   v(i)=sqrt(((n(i)-h)^2)/p);
   VRR(i)=sqrt(((vrr(i)-max(vrr))^2)/p);
  end
end
avarageEvar=sum(VRR)/q
avarageT=sum(TT)/q %miangine zamane residan b bazeye %1 javab behine baraye q matrise ijad shode har kodam p tekrar
```

```
avaragen=sum(nn)/q %miangine tedade tekrar baraye residan b bazeye %1 javab behine baraye q
      matrise ijad shode har kodam p tekrar
avaragevariance=sum(vv)/q %miangin evariance tedade tekrare residan b bazeye %1 javab behine
      dar p tekrar



 function z=objectfunction(w)
global E;
global N;
global t;
global c;
 for j=1:N
           wt(:,j)=w(j).*E(:,j);
 end
 for i=1:t-1
        R(i)=log(sum(wt(i,:)));
 end
 ee=zeros(1,t-1);
 ee(5)=1;
 z=-ee*(sort(R))';
```

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