



Stock Portfolio Optimization Using Water Cycle Algorithm (Comparative Approach)

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ABSTRACT

Portfolio selection process is a subject focused by many researchers. Various criteria involved in this process have undergone alterations over time, necessitating the use of appropriate investment decision support tools. An optimization approach used in different sciences is using meta-heuristic algorithms. In the present study, using Water Cycle Algorithm (WCA), a model was introduced for selecting the optimal portfolio, and then the obtained results were compared with those obtained from Harmony Search (HS) and Imperialist Competitive Algorithm (ICA). For this purpose, using the data of 10-month (April 2016 to January 2017) returns of 50 top companies in the Stock Exchange Market of Iran, the optimal portfolio was estimated using the above-mentioned algorithms with the aim of maximizing profit and minimizing risk, and then the optimal portfolios obtained from these algorithms were compared with each other. Results of implementing these algorithms indicated that despite the high capability of the studied algorithms to optimize the portfolios, WCA algorithm had higher capability of portfolio optimization than the other ones

Keywords:

Meta-heuristic algorithms, stock exchange market of Iran, portfolio optimization.



1. Introduction

One of the major issues in relation with risk reduction in stock exchange market is to create an optimal portfolio. Normally, investors create portfolios in order to maximize their stocks' profit, and thus they select the stocks with the highest return; however, obtaining higher profit is associated with higher risk, and thus investors are coerced to bear more risk in order to achieve more return. Any investor's capital assets vary in accordance with his conditions, time horizon, risks, and expected cash flow. In portfolio management, the objective is to select a set of stocks so that the risk is minimized and profit is maximized. Previously, due to limitation of choices, the problem of selecting the best stocks for investment and creating an optimal portfolio was not as difficult and complicated as it is now; while, currently, creating an optimal portfolio from among the available stocks requires a high level of experience and expertise and necessitates precise investigation and scrutiny. Regarding the growth, diversity, and complexity of the investment environment as well as the increased diversity of companies, investors are facing a wide range of choices, which reveals the necessity of using mathematical models, software, and novel methods and techniques for portfolio optimization.

Researchers have been focusing on portfolio optimization problems since early 1952. The new portfolio theory, which was first introduced by Markowitz (1952), developed an organized paradigm toward creating a portfolio with the highest expected return rate at a certain level of risk (which is a common feature among all the existing portfolios in efficient set). Based on Markowitz's theory, for a certain level of return, you can minimize the portfolio's variance by minimizing the investment risk, or you can increase the expected return of the portfolio at a certain level of risk that can be tolerable for the investor. Theoretically, selecting a portfolio in risk minimization can be solved and executed by applying mathematical formula; however, in practice, it requires extensive calculations, necessitating the use of novel optimization methods and meta-heuristic algorithms. Therefore, due to the high unreliability dominating stock exchange markets, the existence of various orientations and preferences among investors, and successful performance of meta-heuristic algorithms in optimization problems, we have witnessed application of these algorithms as an appropriate method for

optimal portfolio selection in recent years. One of the algorithms, the appropriate performance of which in non-economic optimization problems has been proved, is WCA algorithm, which was introduced by Eskandar et al. (2012). Since this algorithm has not been yet used in economic optimization problems, especially portfolio optimization, and the results obtained from foreign markets can't be generalized to domestic markets, the present research aims at investigating the status of portfolio optimization by this meta-heuristic algorithm and comparing its performance with two older algorithms, namely HS and ICA. Examining the hypothesis that WCA algorithm has better performance in portfolio optimization than HS and ICA is the other objective.

2. Literature Review

The metaheuristic algorithms have been used extensively in the field of economics and finance. For example Mahfoud and Mani (1996) used Genetic Algorithm (GA) to create an appropriate portfolio and estimate the weekly return of stocks. Accordingly, they calculated the return of a selected portfolio at the end of each week and compared it with the return of market indices. Results of this study were compared with those of an ANN¹ system. At the end of each week, the realized return was examined, and so it was indicated that the error and accuracy of the given method was 6.6% and 47.6%, respectively. Lazo et al. (2000) used GA and ANN to select and manage the set of assets in Sao Paulo Stock Exchange market from July 1994 to December 1998. The selected portfolio was managed using this dual genetic-neural system for a 49-week period, and then the obtained results were compared with Bovespa index. Results indicated that the managed portfolio's return derived from the mentioned model was considerably similar to the market index and even higher than it in some cases. Yang (2006) used GA along with a dynamic portfolio optimization system to develop the portfolio's efficiency. The obtained results indicated the efficiency of GA in optimizing the portfolio. Cura (2009) used PSO² algorithm in a constrained portfolio optimization problem. He selected weekly prices of a limited number of stocks in different markets around the world in a 5-year period from 1992 to 1997. Using this technique he depicted the efficient frontier, the results of which indicated successful performance of this technique in portfolio optimization. Hao and Lin

(2009) applied GA as a tool for solving their models in order to select a portfolio with a fuzzy random return. Results showed that GA was successful in solving the model for portfolio selection. Chang et al. (2009) presented a meta-heuristic method for solving portfolio optimization problems, in which GA was applied in different portfolios the risk of which had been calculated in different ways. The obtained results indicated that it would be possible to achieve an optimal portfolio by means of GA. Anagnostopoulos and Mamanis (2011) investigated the multi-objective evolutionary algorithms, including NSGA³, PESA⁴, and SPEA2⁵, for solving the optimal portfolio selection problem. In this research, profit maximization and risk minimization were the objective functions. The obtained results showed that, generally, the evolutionary algorithms are reliable and efficient strategies for such a problem. Jahan and Akbarzadeh-T (2012) proposed the EO-SA (Extremal Optimization) and LA-SA (Learning Automata) algorithms for optimal portfolio selection problem. Results indicated that optimal portfolio selection strategy could lead to increasing convergence speed and improving performance. These results were tested and confirmed in five major stock markets in the world. In order to confirm accuracy of the proposed methods, the convergence speed of the proposed algorithms was compared with other heuristic and meta-heuristic algorithms such as NN⁶, TS⁷, and GA. Sadati and Doniavi (2014) used HS algorithm to solve fuzzy random portfolio selection problem with the aim of increasing the return. Their results implied that the studied evolutionary algorithm was perfectly capable of handling portfolio selection problem. Sadati and Mohasefi (2014) tried to implement ICA algorithm for solving fuzzy random portfolio selection problem with the aim of increasing the return of assets by a fuzzy random variable, the results of which indicated appropriate performance of this algorithm in such a problem. Salahi et al. (2014) focused on selecting an optimal portfolio using PSO and HS algorithms. The test was carried out on five datasets, each of which included 31 to 225 assets. Results showed that HS algorithm had a much faster performance, especially in large datasets, than PSO algorithm. Saborido et al. (2016) used multi-objective evolutionary algorithms, including NSGAI, MOEA/D and GWASF-GA, for fuzzy portfolio selection in Spain. Results of the statistical analysis indicated high performance of

GWASF-GA algorithm. Liu et al. (2016) focused on multi-period fuzzy portfolio selection with bankruptcy control and affine recourse. The optimization objectives were defined as maximizing the terminal wealth and minimizing the cumulative risk and the cumulative uncertainty of the returns of portfolios over the whole investment horizon. To solve the proposed model, a hybrid particle swarm optimization algorithm was designed. Finally, an experimental example was presented to demonstrate application of the proposed model. Comparison of the results indicated effectiveness of the designed algorithm. Mashayekhi and Omrani (2016) used NSGA-II for portfolio optimization with the objectives of maximizing return and minimizing risk of the portfolio; besides, for uncertainty in the proposed model, the asset returns was considered as trapezoidal fuzzy number. The results obtained from 52 firms listed in stock exchange market of Iran showed that the proposed model was superior over DEA and Markowitz's model in terms of considering return, risk, and efficiency. Jalota et al. (2017) used Decision Support System (DSS) for portfolio optimization in India. For this purpose, they used Hybrid Intelligent Algorithm (HIA). To conduct the experimental studies, the data of 2008-2013 was used for training, 2013-2015 for performance testing, and 2015-2016 for validating the optimization models.

In addition to optimizing stock portfolios, Fractional Algorithms for other optimizations and predictions are also used. For example Eskandar et al. (2013) used WCA for optimization of truss's weight, while Baghipour et al. (2014) used this algorithm for optimal allocation in environmental problems. Moreover, Haddad et al. (2014) used WCA for optimal operation of the reservoir system of Karun-4 and a 4-reservoir system in Iran, the results of which showed high convergence and reliability of this algorithm. Sadollah et al. (2015) used WCA for solving constrained multi-objective optimization problems, the results of which indicated that WCA algorithm was a distinct conventional method with an acceptable reliability for finding optimal solutions in problems with different scales. Qaderi et al. (2017) focused on operation of the reservoir system using WCA. The obtained results implied superiority of WCA algorithm over other studied algorithms, including HS and ICA algorithms. Pahnehkolaei et al. (2017) used Gradient-Based Water Cycle Algorithm (GWCA) with evaporation rate in chaos suppression problem. Their

results indicated that the proposed algorithm had an excellent performance compared to other optimization algorithms including GA, DE, PSO, and ICA. Heidari et al. (2017) used Gaussian bare-bones Water Cycle Algorithm (NGBWCA) for optimal reactive power dispatch (ORPD) in electrical power systems. The objective was to minimize voltage deviations and resistive loss. The experimental results and statistical tests explicitly showed efficiency of NGBWCA in solving ORPD problem. Anand and Suganthi (2018) optimized Artificial Neural Network (ANN) using a hybrid algorithm of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). The hybrid GA-PSO algorithm has been used to improve the estimation of electricity demand of the state of Tamil Nadu in India. Using the historical demand data of 25 years from 1991 till 2015 it is found that ANN-GA-PSO models have higher accuracy and performance reliability than single optimization models such as ANN-PSO or ANN-GA. Mohammadian, Lorestani and Ardehali (2018) developed and examined the applicability of a newly developed evolutionary particle swarm optimization (E-PSO) algorithm for optimization of the ED problem, where practical constraints, namely, valve-point effects, prohibited operating zones, multiple fuel usage, dynamic ramp rate limits, transmission losses, tie-line capacity, and spinning reserve are considered. They findings that the proposed features enable the E-PSO algorithm to successfully optimize the ED problem in lower simulation time, while all constraints are met. Zhang, Lihui; Ge, Riletu and Chai, Jianxue (2019), applied the Tabu search (TS) algorithm to the least square to support vector machine (LSSVM) optimized by the particle swarm optimization (PSO) algorithm to forecast China's energy consumption. They demonstrated that the proposed TS-PSO-LSSVM forecasting model had higher prediction accuracy, generalization ability, and higher training speed and then applied the TS-PSO-LSSVM forecasting model to forecast the energy consumption of China from 2017 to 2030.

3. Methodology

In the present paper, the optimal portfolio was created using WCA, HS, and ICA algorithms, which will be introduced in this section. Since WCA is a new algorithm and has been used less than the two other ones, it will be explained in more details, but the two

other algorithms will be explained in short in order to avoid the article being too long.

3.1. Water cycle algorithm (WCA)

WCA algorithm is a meta-heuristic algorithm presented by Eskandar et al. (2012) based on water cycle or hydrological cycle in nature. The fundamental concepts of this method were based on the observations from water cycle process and stream of the rivers to seas in the real world (Eskandar et al., 2012). Similar to other Meta-heuristic algorithms, WCA starts with an initial population, i.e. raindrops. First, it is assumed that there is a certain amount of rain. In this way, the best raindrop is selected as the sea, some of good raindrops are considered as rivers, and the remaining raindrops are taken for streams that flow into the rivers and the sea. In an N_{var} dimensional optimization problem, one raindrop is an array in the form of $I \times N_{var}$. This array is defined as:

$$\text{Raindrop} = [X_1, X_2, X_3, \dots, X_{N_{var}}] \quad (1)$$

Where, $X_1, X_2, \dots, X_{N_{var}}$ are decision variables. In order to start the optimization procedure, the matrix of raindrops with size of $N_{pop} \times N_{var}$ is generated randomly similar to equation (2).

$$\begin{aligned} &\text{Population of raindrops} \\ &= \begin{bmatrix} \text{Raindrop}_1 \\ \text{Raindrop}_2 \\ \vdots \\ \text{Raindrop}_{N_{pop}} \end{bmatrix} \\ &= \begin{bmatrix} X_1^1 X_2^1 X_3^1 & \dots & X_{N_{var}}^1 \\ \vdots & \ddots & \vdots \\ X_1^{N_{pop}} X_2^{N_{pop}} X_3^{N_{pop}} & \dots & X_{N_{var}}^{N_{pop}} \end{bmatrix} \end{aligned} \quad (2)$$

Where, N_{pop} and N_{var} are the number of raindrops (population size) and the number of decision variables, respectively. The costs of raindrops are obtained by the evaluation of cost function (C_i) in equation (3).

$$\begin{aligned} C_i = \text{Cost}_i &= f(X_1^i, X_2^i, X_3^i, \dots, X_{N_{var}}^i) , i \\ &= 1, 2, 3, \dots, N_{pop} \end{aligned} \quad (3)$$

Next, N_{pop} raindrops are created. A N_{SR} number of the best raindrops (minimum values) are selected as the sea and rivers. The raindrop with the minimum

value is considered as the sea. In fact, N_{SR} is the sum of number of rivers (which is a user parameter) and a single sea (equation 4). The rest of the population (raindrops form the streams which flow into the rivers or may directly flow into the sea) are calculated through equation (5).

$$N_{SR} = \text{Number of Rivers} + \overset{\text{sea}}{1} \quad (4)$$

$$N_{Raindrops} = N_{pop} - N_{SR} \quad (5)$$

Depending on the flow intensity, equation (6) is used for raindrops to be designated/assigned to rivers the sea.

$$NS_n = \text{round} \left\{ \left(\frac{Cost_n}{\sum_{i=1}^{N_{SR}} Cost_i} \right) \times N_{Raindrops} \right\}, n = 1, 2, \dots, N_{SR} \quad (6)$$

Where, *round* = function that rounds the value of the function within the bracket to the closest integer number; and N_{Sn} is the number of streams that flow into specific rivers or the sea. A stream flows to the river along the connecting line between them using a randomly chosen distance as equation (7).

$$X \in (0, C \times d), \quad C > 1 \quad (7)$$

Where, *C* is a value between 1 and 2. The best value for *C* is 2 (Eskandar et al., 2012). *d* is the distance between the stream and river. The value of *X* in equation (7) corresponds to a distributed random number between 0 and (*C*×*d*). If the value of *C* becomes greater than 1, the streams are able to flow in different directions towards the rivers. New position of streams and rivers are calculated through equations (8) and (9).

$$X_{Stream}^{i+1} = X_{Stream}^i + rand \times C \times (X_{River}^i - X_{Stream}^i) \quad (8)$$

$$X_{River}^{i+1} = X_{River}^i + rand \times C \times (X_{Sea}^i - X_{River}^i) \quad (9)$$

Where, *rand* is a uniformly distributed random number between 0 and 1. If the solution given by a stream is better than its connecting river, the position

of river and stream will be exchanged (i.e. the stream will become a river and vice versa). This exchange can similarly occur for rivers and the sea. One of the most important factors that prevent rapid convergence of algorithms and being trapped in local optima is evaporation. Evaporation process causes the sea water to evaporate as rivers or streams flow into the sea. The below Pseudocode demonstrates whether the river flows into the sea or not.

if $|X_{Sea}^i - X_{River}^i| < d_{max}$, *i*
 = 1,2,3 ..., $N_{SR} - 1$
 → Evaporation and rain process → end

Where, d_{max} is a small number close to 0. Therefore, if the distance between river and sea is less than d_{max} , it implies that the river has joined the sea. In this condition, evaporation process is applied and after sufficient evaporation, rain will start similar to nature. A large value for d_{max} reduces the search while a small value encourages the search intensity near the sea. Thus, d_{max} controls the search intensity near the sea (optimal solution). The value of d_{max} adaptively decreases in each step as:

$$d_{max}^{i+1} = d_{max}^i - \frac{d_{max}^i}{\text{max iteration}}$$

During the process of raining new raindrops form new streams in different locations. Equation (12) is used to determine the new locations of streams.

$$X_{Stream}^{new} = LB + rand \times (UB - LB)$$

Where, *LB* and *UB* are lower and upper bound in the problem, respectively. The best new raindrops are considered as a river and the rest of raindrops are accounted for new streams flowing into the rivers or they may directly flow into the sea. To enhance the convergence rate and computational performance of the algorithm, equation (13) was used only for the streams which directly flow into the sea.

$$X_{Stream}^{new} = X_{Sea} + \sqrt{\mu} \times \text{Randn}(1, N_{var}) \quad (9)$$

Where, μ is a coefficient which demonstrates the range of the search region near the sea and *Randn* is

the normally distributed random number. The larger value for μ increases the possibility of exiting feasible region. The smaller value for μ forces the algorithm to search in smaller region near the sea. Eskandar et al. (2012) proposed that the suitable value for μ is 0.1. In this study, the convergence criterion for each run was considered to be satisfied whenever the maximum number of iteration reaches 1000.

3.2. Imperialist Competitive Algorithm (ICA)

This algorithm starts with a number of random initial populations, each of which is called a country. Some of the best elements of the population (countries with minimum value of cost function) are considered as imperialists, and the rest of population form the colonies, each of which belong to one imperialist. The imperialists, depending on their power, absorb these colonies toward themselves through a specific procedure. During movement toward an imperialist country, some of these colonies might achieve a position better than the imperialist (lower cost than the imperialist). In this case, the imperialist country and the colony interchange their positions, and this algorithm continues with the imperialist country in the new position. Now, this new imperialist country begins to impose the homogenization policy on its colonies. In each repetition of the algorithm the weakest imperialist loses one or more of its weakest colonies, so that a competition occurs among the imperialists to own these colonies. After a while, all the imperialists fall down and there will be only one imperialist, which will control all other countries. In such a case, the competition will terminate (Atashpaz-Gargani and Lucas, 2007).

3.3. Harmony Search (HS) algorithm

This algorithm is based on the principles and behavior of musicians who cooperate with each other to create a piece of music and try to select the best choice among different notes in order to create the best music. In this regard, musical instruments can be considered as decision variables in an optimization problem. In music, in order to accomplish the best performance, each rehearsal is compared with the previous one, and at each repetition, the new piece of music is memorized. If the new music is better than

the worst music saved in the memory, it will replace it, and so the worst music will be removed from the memory; however, if the new music is not better than the worst music in memory, then the algorithm will go to the next repetition without any replacement. This process will be repeated until the best piece of music is achieved (Geem, 2006).

3.4. Research method

With regard to the increasing necessity of stock portfolio optimization, on the one hand, and the application of WCA optimization algorithm in other sciences, on the other hand, the present study aims at investigating the efficiency of this algorithm in optimization of the stock portfolio. The input data for implementing the proposed algorithm included the information of 50 top companies in Iran Stock Exchange market in a time period from April 2016 to January 2017. For this purpose, a model was developed based on WCA, HS, and ICA algorithms in MATLAB software in order to obtain portfolio optimization results and compare the performance of WCA with the two other algorithms.

To achieve the objectives of this study, after selecting the data of active companies in stock exchange market, a multi-objective model, with objectives of return maximization and risk minimization, was designed to select the portfolio among 50 top companies in the stock exchange market; then, the designed model was solved using meta-heuristic algorithms, including WCA, HS, and ICA.

The list of 50 top companies in Iran Stock Exchange market investigated in this study is presented in Table (1).

Table-1: List of 50 active companies in Iran Stock Exchange market

decision variable	company	decision variable	company
X1	Gulf Petrochemical Industries	X26	Chador Malu
X2	Iran Khodro	X27	Bahman Group
X3	Saipa	X28	Informatics services
X4	Bandar Abbas Oil Refining	X29	Pension fund investment
X5	Mobarakeh Steel Sepahan	X30	Development of mines and metals
X6	Mobile communication company	X31	National Development Investment Group
X7	Iran Telecommunication	X32	S.Iranian Petrochemical
X8	Ghadir Investment	X33	Saipa Diesel
X9	Oil and Gas Corp	X34	Steel of Khuzestan
X10	Investment and Petrochemical Supply	X35	Leasing Ryan Saipa
X11	Shipping of the Islamic Republic	X36	Atiyeh investment
X12	Azarab Industries	X37	Ansar Bank
X13	Jam Petrochemical	X38	Iran Khodro Investment Development
X14	Iranian Copper Industries	X39	Supply Pharmaceutical Investment
X15	Esfahan Oil Refining	X40	Kharazmi Investment
X16	Saipa Investment	X41	North Cement
X17	Mobin Petrochemical	X42	Fars and Khuzestan cement
X18	Rena Investment	X43	Casting sand
X19	Pars Khodro	X44	Development and Construction of Kerman Province
X20	Zamyad	X45	Construction and development of Fars
X21	Fajr Petrochemical	X46	Zangan industry
X22	Iran Transfo	X47	Bafgh mines
X23	Golghar Mineral and Industrial	X48	Bama
X24	Omid Investment Management Group	X49	North drilling
X25	Pardis Petrochemicals	X50	Sahand Rubber Industries

Regarding the multi-objectiveness of the problem, the model elements (decision variables, objective functions, and limitations) for designing a multi-objective model are described below:

3.5. Decision variables

In a systemic view, the main part of the outputs of a mathematical model is its decision variables. In this research, decision variable of the mathematical model, based on the defined characteristics, is X_i that indicates the amount of investment on the i^{th} stock.

3.6. Constant values of the mathematical model (parameters of model):

Designing any mathematical model requires some certain values that affect its solution results as inputs of the model. The technical coefficients of limitations and coefficients of the variables used in the objective function are input elements of the mathematical model. The constant values, which should be determined from

the collected documents and data analysis before solving the model, include:

(a) Systemic limitations

This limitation means that the purchased stocks must be exactly equal to the total available resources. This limitation is demonstrated in the model as follows:

$$\sum_{i=1}^n X = 100 \quad (14)$$

(b) Limitation of maximum investment on the stocks

By determining an upper limit for the decision variable, diversity of the stocks constituting the portfolio can increase and a portfolio with a higher diversity can be achieved. While determining the upper limit for the decision variable, the investor's opinion is a determining factor, and thus the upper limit is determined with regard to the minimum stocks on which the investor tends to invest.

$$X_i \leq U, \quad i = 1, 2, 3, \dots, n \quad (15)$$

(c) Limitation of borrowing sales

In developed capital markets, the investor can offer for selling a stock, which he doesn't own. This is called borrowing sales. If the borrowing sale is prohibited, it will be demonstrated in the model as the following limitation:

$$X_i \geq 0, \quad i = 1, 2, 3, \dots, n \quad (16)$$

This limitation assumes the minimum weight of each stock in the portfolio equal to zero and rejects the negative numbers. If the borrowing sale is allowed, this limitation will be eliminated.

3.7. Objectives of the deigned model

(a) Maximum return of the portfolio

Since investment is made to achieve return and the investor tends to invest his budget in such a way to achieve the maximum return, the objective corresponding to the portfolio return is defined as follows:

$$\text{Max } Z_1 = \sum_{i=1}^n x_i r_i \quad (17)$$

Return of investment on stocks, in a certain period, includes any kind of received cash plus the price changes during the period divided by the price of securities or assets at the time of purchase. The return rate is calculated through the following equation:

$$r_t = \frac{D_t + (P_t - P_{t-1})}{P_{t-1}} \quad (18)$$

(b) Minimum risk of portfolio

Since risk was defined as return variability, the more limited the return distribution is, the less the investment risk will be. In practice, the criterion of return rate, which indicates the features of probability distribution, is used to measure risk. Since variance represents dispersion of the data round the mean, minimizing variance as an objective for reducing the portfolio return variability is defined as follows:

$$\text{min } Z_2 = \sum_{i=1}^n x_i^2 \delta_i^2 + \sum_{i=1}^n \sum_{j=1}^n x_i x_j \delta_{ij} \quad (19)$$

4. Results

4.1. Algorithms Verification

In order to evaluate the efficiency and validation of the author's developed algorithms, a set of standard benchmark functions was selected, as presented in Table (2).

The performance of WCA algorithm in solving these functions was compared with the performance of other developed meta-heuristic algorithms including HS and ICA. In this way, the population size as well as the number of evaluations of benchmark functions in all algorithms was identical, and proportional to the dimensions of each function. According to Table (2), for the benchmark functions with lower dimensions, the performance of all algorithms was approximately similar together, but for high dimensions problems (Rosenbrock function with dimensions of 10 and 30), the WCA algorithm was the only algorithm which was capable of solving the problem, while the performance of other meta-heuristic algorithms declined and they diverged from the optimal value. As shown, the values resulting from WCA were the closest to the optimal value.

Table-2: Performance of developed algorithms in solving the benchmark functions

Function	Dimensions	Optimal value	WCA	HS	ICA
Goldsten-Price	2	3	3	3	3
McCormick	2	-1.9133	-1.9132	-1.9132	-1.9132
Six-Hump Camel	2	-1.0316	-1.0316	-1.0316	-1.0316
Shekel	4	-10.5364	-10.532	-6.4619	-10.532
Rosenbrock	2	0	8.9×10^{-9}	1.08×10^{-6}	2.7×10^{-15}
Rosenbrock	10	0	4.06×10^{-7}	1.43	0.055
Rosenbrock	30	0	2.82×10^{-6}	63.03	2.11

By successful verification of WCA algorithm by benchmark functions, it is now possible to use it for optimization of Stock Exchange Portfolio problem.

This section deals with selecting the optimal portfolio among 50 top companies in the stock exchange market. Table (1) represents these 50 companies along with the variables defined for them as well as the parameters required for implementing the model.

Regarding the problem dimensions, the number of initial population in the studied algorithms was assumed equal to 100. The best values of the objective

function (return maximization and risk minimization) obtained from 10 different runs of the algorithms, including WCA, HS, and ICA, were 143927353.11, 409574043.64, and 380743529.97, respectively. The number of repetitions in the three algorithms was considered equal to 100, and also the number of evaluations of the objective function in the three algorithms was considered the same and equal to 10100. The convergence diagram of the studied algorithms in implementation of the portfolio selection model is represented in Figure (1).

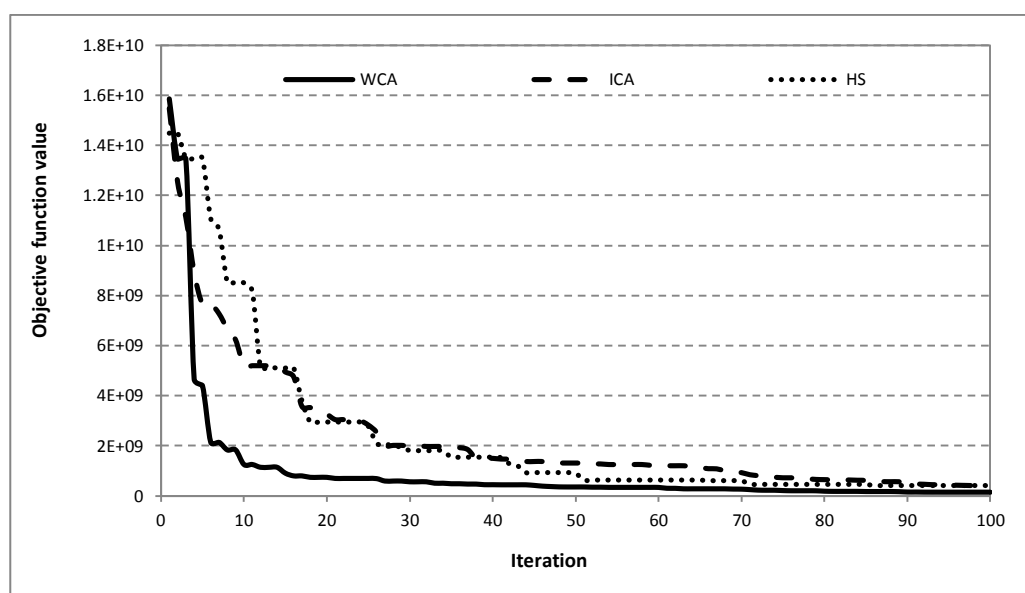


Figure-1: Convergence of the algorithms in selecting the optimal portfolio

As seen in Figure (1), WCA algorithm converged faster than the two other algorithms, and could approach the objective function to the optimal value. Furthermore, it performed the computations much faster than the two other algorithms; so that, as indicated by the results, WCA algorithm with the time of 1034.97 seconds had a higher speed, especially in problems with higher dimensions, compared to HS and ICA algorithms with the time of 2794.95 and 2438.31 seconds, respectively.

The results obtained from applying the studied meta-heuristic algorithms are presented in Table (3). The presented solutions indicate a proportion of the

budget, which must be invested in the stocks of any company. For example, the investment rate in Iran Khodro Company (X_2) derived from WCA was equal to 1.112%, which indicates that the investor must invest 1.112% of his capital on variable X_2 (Iran Khodro Company) in order to minimize the fitness function.

Table 3: Results of application of the studied algorithms

decision variable	WCA	HS	ICA	decision variable	WCA	HS	ICA
X1	0.006128	0	0.130586	X26	1.89E-05	6.830598	0
X2	1.112349	1.456062	1.477009	X27	0.011394	0.167776	0.705273
X3	0.002884	0.259361	0.474773	X28	0.003465	2.09888	0.194053
X4	0	1.234239	5.751035	X29	4.987551	0.30789	3.761482
X5	9.964984	2.13347	4.458967	X30	0.71485	5.302262	1.974288
X6	0.002631	2.012677	0.017918	X31	0.006833	0.100438	2.713003
X7	9.963312	0.591934	0.362669	X32	0.430912	0	0
X8	0.633809	0.154666	3.884969	X33	0.671532	0	0.720819
X9	0.494469	0.118144	0.140031	X34	0	6.007381	1.351661
X10	9.850515	0.115186	4.005152	X35	0.001632	0	0.002513
X11	0.027404	0.259108	0	X36	0.000315	4.629976	0.026514
X12	2.19E-05	0.008285	0.323934	X37	0.235352	0.258664	1.045946
X13	0.025133	1.09345	0	X38	9.889131	6.007998	3.433995
X14	9.774169	6.247877	7.271767	X39	0	0.023191	8.132811
X15	0	2.500925	5.200994	X40	0	0.13821	3.392441
X16	0	0	0.176228	X41	0.150079	0.351988	3.700108
X17	9.961544	0.139429	3.31978	X42	9.574586	0.522838	0.25498
X18	0.031444	0	2.834849	X43	0.00345	6.688885	0.291057
X19	0.723465	0.01986	5.838376	X44	3.99E-05	6.360313	0
X20	9.943548	0.32799	3.833037	X45	0.004915	0.187637	5.954934
X21	0.003009	0.006013	0	X46	0.000711	6.782621	0.000701
X22	1.78E-05	5.614001	0.067858	X47	0	6.840926	0.000383
X23	2.628172	5.317596	5.840122	X48	0	6.840926	0
X24	8.01632	2.522985	4.443217	X49	0.121879	0	1.333277
X25	0.026024	0.535099	0.671755	X50	0	0.882242	0.484734

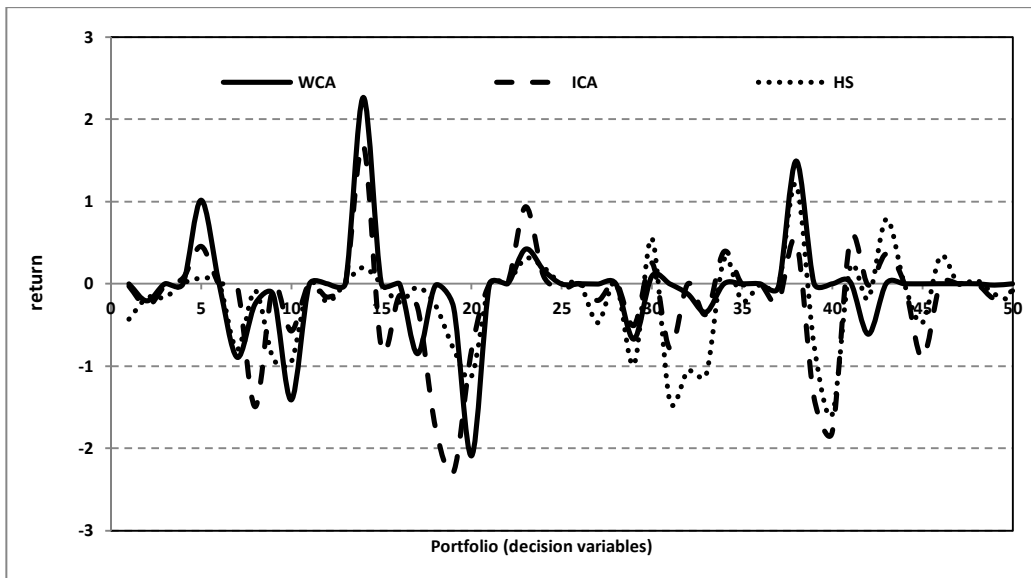


Figure-2: Comparing the return obtained from studied algorithms for each stock

Figure (2) represents a diagram comparing each stock in the studied period (April 2016 to January 2017), which has been derived from the meta-heuristic algorithms.

As seen in Figure (2), WCA algorithm had a better performance in increasing the return of each stock in the optimal portfolio selection problem compared to the two other algorithms.

Figure (3) represents a diagram comparing the risk of each stock in the studied period (April 2016 to January 2017), which has been derived from the studied algorithms.

As seen in Figure (3), WCA algorithm had fewer risks than the two other algorithms; besides, intensity of the risks in WCA was lower than that in the two other ones.

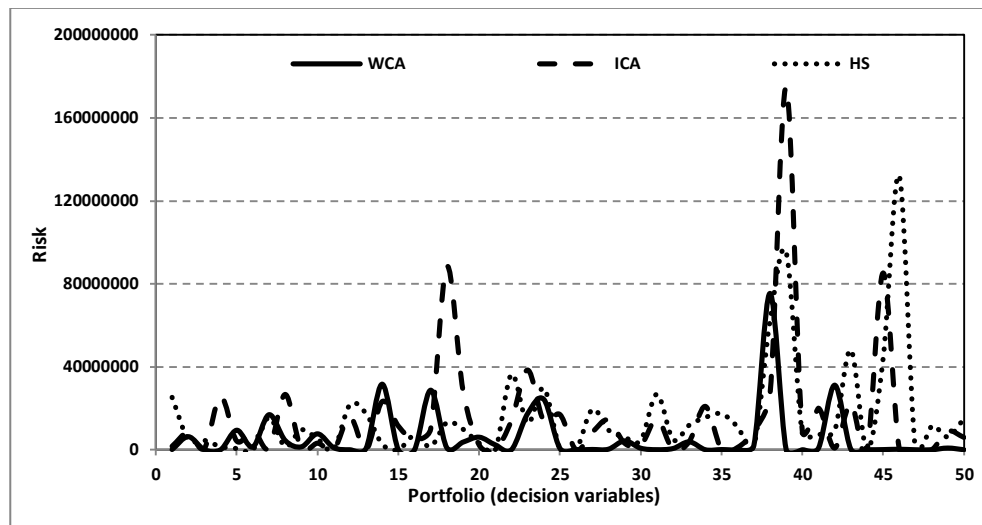


Figure-3: Comparing the risk obtained from studied algorithms for each stock

5. Discussion and Conclusions

In the present paper, it was attempted to perform a comparative investigation of the three meta-heuristic algorithms, including WCA, HS, and ICA, for optimization of portfolios of 50 top companies in Iran Stock Exchange market. The obtained results indicated that the WCA-based model, which had previously exhibited good functional capability and accuracy in solving constrained multi-objective problems as well as optimization of structure design problems, had good efficiency in portfolio optimization problems as well. Comparing the procedure of modeling this algorithm with the two other algorithms, besides confirming the previous results, showed that this algorithm had better compatibility in terms of compatibility with standard benchmark functions in the validation phase compared to HS and ICA algorithms. Subsequently, performance of this algorithm in optimizing the portfolio of Iran Stock Exchange market was investigated. Since the

objective functions were defined as minimization of risk and minimization of minimum return (symmetry of return maximization), the results obtained from solving the problem indicated the appropriate performance of WCA algorithm compared to the two other ones; the best objective function values resulted from 10 different runs of WCA, HS, and ICA algorithms was obtained equal to 143927353.11, 409574043.64, and 380743529.97, respectively. Another reason for superiority of WCA algorithm over the two other ones was the speed of computations, in a way that the results showed this algorithm with the time of 1034.97 seconds had higher speed, especially in problems with higher dimensions, compared to HS and ICA algorithms with the time of 2795.95 and 2438.31 seconds, respectively.

Since the model of the presented meta-heuristic algorithms is nonlinear, and due to the fact that it can be used for a large number of variables and also can be

easily updated by adding a new variable (company), it is a more appropriate model for optimal portfolio selection.

Regarding the results obtained from executing the given meta-heuristic algorithms on 50 top companies in Iran Stock Exchange market, the capability of these algorithms is explicitly visible; the results were in an appropriate range, leading to a reliable solution. Furthermore, the use of WCA algorithm led to more acceptable results, which indicated the higher capability of this algorithm compared to the two other ones. In fact, the obtained results imply the acceptance of the investigated hypothesis stating the better performance of WCA algorithm than HS and ICA algorithms.

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Notes

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- ¹ Artificial Neural Network
 - ² Particle Swarm Optimization
 - ³ Non-dominated Sorting Genetic Algorithm
 - ⁴ Pareto Envelop-based Selection Algorithm
 - ⁵ Strength Pareto Evolutionary Algorithm 2
 - ⁶ Neural Network
 - ⁷ Tabu Search