Ant Colony Optimization Approach to Portfolio Optimization – A Lingo Companion

Kambiz Forqandoost Haqiqi and Tohid Kazemi

Abstract—**The purpose of this paper is to apply ACO approach to the portfolio optimization mean–variance model. The problem of portfolio optimization is a multiobjective problem that aims at simultaneously maximizing the expected return of the portfolio and minimizing portfolio risk. Present study is a heuristic approach to portfolio optimization problem using Ant Colony Optimization technique. The test data set is the monthly prices since *2008/20/03* up to *2011/20/03* from Tehran stock exchange. The performance of ACO is compared with *frontcon* function of *MATLAB* software as an exact method. Further more in an attempt to improve the algorithm performance, risk values obtained by ACO approach, were compared with *Lingo* optimal results.**

The results show that proposed ACO approach is reliable but not preferred to an exact method. According to the significant difference between the risk values of ACO and optimal ones, next studies could emphasize on the risk optimization process of proposed ACO.

Index Terms—**Portfolio Optimization, Ant Colony Optimization (ACO), Multiobjective Optimization.**

I. Introduction

Financial markets represent a complex, ever-changing, environment in which a population of investors is competing for profit [1]. Ants as social insects have long inhabited such environments. They have cooperated and competed for resources to survive. These common characters could be inspired to tackle the task of survival in financial jungle.

One of the vital problems in financial markets is Portfolio Optimization Problem (POP) that has received a lot of attention in recent decades. Harry M. Markowitz was the first to come up with a parametric optimization model to this problem, which meanwhile has become the foundation for Modern Portfolio Theory (MPT) [2]. The problem usually has two criteria: expected return is to be maximized, while the risk is to be minimized [3].

In the other words POP presents a multiobjective problem that could be solved with metaheuristic approaches that inspired by ants' behaviors.

In present paper we will use the standard Markowitz model as a multiobjective problem solving model, in order to design an algorithm that is based on Ant Colony Optimization (ACO) approach. Present paper is structured as follows: First importance of this study and summery of POP is presented. A brief literature review is provided in section II, followed in section III by problem description. In section IV ACO approach is explained and proposed algorithm is presented. Empirical study is presented in section V. The paper concludes in section VI with conclusion.

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K. F. Haqiqi is faculty member with Department of Economics and Accounting, Iran Islamic Azad University, Central Tehran Branch, Tehran, Iran.

T. Kazemi is PhD student of Accounting with Department of Economics and Social Science, Shahid Chamran University Of Ahvaz, Ahvaz, Khozestan, Iran (e-mail: drtohid.acc@gmail.com).

II. Literature Review

Studies in usage of Ant Colony Optimization in finance seem quite limited. Therefore we could only point to the few studies that, we were acquainted with.

1) Maringer addressed the issue of finding an optimal portfolio structure when there is a limit on the number of different assets that may be included. He used Ant systems, empirical studies were performed for NYSE, FTSE, and DAX data. The results confirmed that small portfolios can indeed be very well diversified – provided the asset and weight selection has been done with a suitable method [4].
2) Wang and Yang worked on securities-investment market's situation of China, proposed an objective model of the securities investment combination optimization under conditions of the nonnegative investment ratio, and designed ant group algorithm to solve this model's continual optimization. Through the example of computer simulation, they could see that this algorithm was effective in solving the multiobjective programming and in optimizing portfolio investment's application [5].
3) Eslami Bidgoli et al used Ant Colony Optimization to solve portfolio optimization problem with cardinality constrain on the maximum number of assets on Tehran Exchange Market. The results showed that a small portfolio of assets could be found having a comparable performance with much diversified portfolios [6].
4) Forqandoost Haqiqi and Kazemi suggested an algorithm to apply ACO approach to the portfolio optimization mean-variance model. The test data set was the monthly prices from Tehran Stock Exchange. Results confirmed the reliability of proposed ACO. Yet more attempts are needed to improve its performance [7].

In present study presents a more elaboration is made on ACO and investigation is made on risk values obtained by ACO algorithm, as initially suggested by Forqandoost Haqiqi and Kazemi in previous article.

III. Portfolio Optimization

In 1952, Harry Markowitz published a paper on portfolio selection. He divided portfolio selecting process in two stages. The first stage starts with observation and experience and ends with beliefs about the future performances of available securities. The second stage starts with the relevant beliefs about future performances and ends with the choice of portfolio [8].

A. Problem Description

The basic mean–variance portfolio selection problem we consider in present paper can be formalized as follows:

$$\max R_p = \sum_{i=1}^{n} r_i x_i \qquad (1)$$

$$\min \sigma_p = \sqrt{\sum_{i=1}^{n} \sum_{j=1}^{n} x_i x_j \sigma_{ij}} \qquad (2)$$

Subject to:

$$\sum_{i=1}^{n} x_i = 1 \quad \text{and} \begin{cases} x_i > 0 & \forall i \in p \\ x_i = 0 & \forall i \notin p \end{cases} \qquad (3)$$

$$p \subset M \qquad (4)$$

where:

Rp : return of portfolio

r_i : expected return of stock i

x_i : weight of stock i in portfolio

σ_{ij} : covariance between stock i and j

M={1,2,…,N} that N is the number of assets in market.

Equation (1) maximizes the profit associated with the portfolio. Equation (2) minimizes the total standard deviation (the risk) associated with the portfolio. The purpose is to determine value of x_i, that optimizes the objective functions.

IV. Ant Colony Optimization Approach

One of the first behaviors studied by entomologists was the ability of ants to find the shortest path between their nest and a food source. From these studies and observations followed the first algorithmic models of the foraging behavior of ants, as developed by Marco Dorigo [9].

A. Ant's Foraging Behavior

Dorigo and Gambardella (1996) explained, ants foraging behavior in 4 steps as following. As Fig.1(a) shows, ants are moving on a straight line that connects a food source to their nest. Ants deposit on the path a certain amount of pheromone while walking, and each ant probabilistically prefers to follow a direction rich in pheromone.

This elementary behavior of real ants can be used to explain how they can find the shortest path that reconnects a broken line after the sudden appearance of an unexpected obstacle has interrupted the initial path. As Fig.1(b) presents, once the obstacle has appeared, those ants which are just in front of the obstacle cannot continue to follow the pheromone trail and therefore they have to choose between turning right or left.

In this situation we can expect half the ants to choose to turn right and the other half to turn left. A very similar situation can be found on the other side of the obstacle. Fig.1(c) shows the behavior.

It is interesting to note that, those ants which by chance choose, the shorter path around the obstacle will more rapidly reconstitute the interrupted pheromone trail compared to those which choose the longer path. Thus, the shorter path will receive a greater amount of pheromone per time unit and in turn a larger number of ants will choose the shorter path. As Fig.1(d) presents, due to the positive feedback process, all the ants will rapidly choose the shorter path [10].

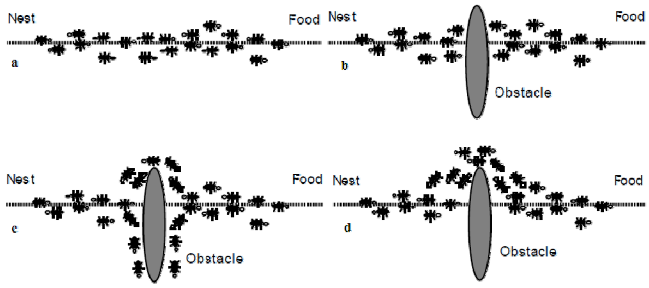

Fig. 1. Ant's foraging behavior [10].

B. Ant's Foraging Basic Algorithm

As Brabozan and O'Nell explained (2007), ant colony optimization (ACO) uses metaphorical inspiration from ant behaviors to create algorithms for optimization purposes. At the start of the algorithm, all the potential solution fragments have their pheromone initialized to a non-zero value. Each ant in turn commences a traversal of the potential solution fragments, in order to build a complete solution. There are many possible ways to implement the construction process. At each decision juncture when a solution is being constructed an ant could simply select from the set of available solution fragments the fragment which has the highest pheromone level. This corresponds to a greedy search process [1].

However, this would tend to result in rapid convergence to a small set of solutions. Another possibility is to stochastically choose amongst the discrete solution fragments available at each step of the construction process. For example, the probability of choosing fragment i from amongst the K possible choices at a particular construction step could be determined using (5). τ_k is the quantity of pheromone associated with fragment k.

$$prob_i = \frac{\tau_i}{\sum_{k=1}^{k} \tau_k} \qquad (5)$$

This approach ensures that while solution fragments which have been part of good solutions in the past are more likely to be selected as their pheromone levels are high, an ant still has the potential to explore a new path. A more complex approach is to combine the pheromone information with an estimate of the likely quality of each of the solution fragments when making the choice of which fragment to add to the growing solution. This is known as adding visibility to the construction process [1].

After all the ants have traversed the solution fragments and have constructed solutions to the problem, the quality of each of these solutions is assessed, and this information is used to update the pheromone trails. The update process typically consists of an evaporation step, and a pheromone deposit step:

$$\tau_i(t+1) = \tau_i(t)(1-\gamma) + \delta_i \tag{6}$$

In the evaporation step the pheromone associated with every solution fragment is degraded, where the evaporation rate is given by γ. The evaporation rate crucially controls the balance between exploration and exploitation in the algorithm. If γ is close to 1, then the pheromone values used in the next iteration of the algorithm are highly dependent on the good solutions from the current iteration, leading to local search around those solutions. Smaller values of γ allow solutions from earlier iterations of the algorithm to influence the search process [1].

The amount of pheromone deposited on each solution fragment *i* during the pheromone update process depends on how the deposit step is operationalized in the algorithm. One method is to reinforce the components in the solution found by each ant by adding $Q * F$ to the pheromone associated with each solution fragment, where Q is a modeler-chosen fixed amount of pheromone, and F is a measure of the quality of the solution scaled into the range 0 to 1.

Therefore, solution fragments contained in good-quality solutions are more heavily reinforced by pheromone. The algorithm is terminated either after a fixed number of iterations, or when there has been no improvement in the best solution for a set number of iterations [1].

C. Applying the Algorithm

For optimization purpose of POP, a metaphorical inspiration from ant behavior is needed. Therefore, as Table.I presents, solution space could be described as a vector with n members, which points to number of stocks in the market. This vector is called stock vector. The main object is allocating proper coefficients to each member of stock vector. Therefore coefficient vector would be introduced as *c*= [*0, 1, 2, ..., k*]. Allocating 0 to each stock means, that stock does not participate in portfolio and a value of more than 0 means that stock would be a participant in portfolio.

TABLE.I: SOLUTION SPACE DESCRIPTION

Stock number	1	2	3	…	n-1	n

The proposed algorithm is based on pheromone trail. Saved information about density of solution fragments, guide ants to proper path choice. This collective memory is known as pheromone matrix. Pheromone matrix contains *n* culms and *m* rows. Where *n* is the number of stocks and *m* points to coefficient vector members. Table.II presents the pheromone matrix, where rows refer to coefficient vector and columns refer to stock vector.

TABLE.II: PHEROMONE MATRIX

	1	2	…	*n*
0	τ_{01}	τ_{02}		τ_{0n}
1	τ_{11}	τ_{12}		τ_{1n}
…				
m	τ_{m1}	τ_{m2}		τ_{mn}

To continue, each member of stock vector should be assigned a weight in the set. Algorithm does this duty with employing coefficient vector. The probability of coefficient allocation could be determined as:

$$p_c = \frac{\tau_{cs}}{\sum \forall_c \, \tau_{cs}} \tag{7}$$

Ants use this strategy to select a proper portfolio. After, all the ants have constructed solutions to the problem, the quality of each of these solutions is assessed, and this information is used to update the pheromone trails. For each portfolio, a fitness value would be calculated using (8):

$$fitness\ function = \frac{R_p}{\sigma_p} \tag{8}$$

The best fitness value points to the best portfolio. System could recognize the best value and starts to update the pheromone trail information according to the best portfolio. The update process could be presented as following:

$$\tau_{cs}(t+1) = \tau_{cs}(t)(1-\gamma) + \delta_{cs} \tag{9}$$

And

$$\delta_{cs} = Q.\frac{\dfrac{R_p}{\sigma_p}}{\dfrac{R_{p^*}}{\sigma_{p^*}}} \tag{10}$$

where:

γ : evaporation rate

p^* : best portfolio

Q : fixed amount

The algorithm ends after a prefixed number of iterations. The proposed algorithm could be performed in 3 major steps as follows:

1. Coefficient Allocation
2. Quality Assessing
3. Updating

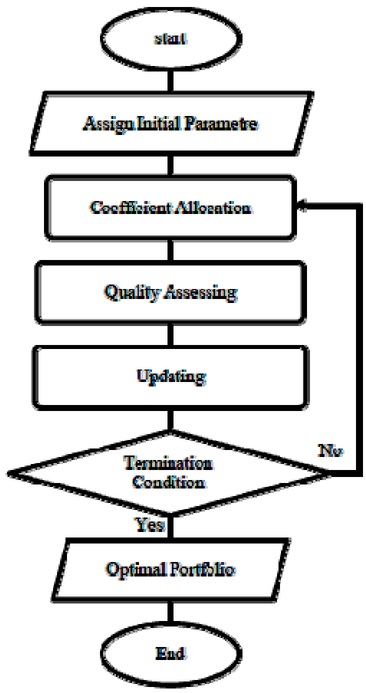

Fig. 2: Block Diagram of Proposed Ant Algorithm.

Fig. 2 presents proposed algorithm diagram.

V. Empirical Study

A. Data

The empirical study in this paper is based on data set in Tehran Stock Exchange (TSE). Data set is the monthly prices over the period 2008/20/03 up to 2011/20/03. Out of quoted companies in TSE, 30 companies, participating in TEFIX 30, were chosen in order to test the performance of algorithm. Brabozan and O'Nell (2007) underlined the effect of the collected data quality on a model success.

Out of 30 companies, 6 of them were not fully active in predefined time period. Table.VI (Appendix) presents, the expected return of remaining 24 companies of predefined set. The expected return computed for the period of 3 companies, were negative. So these companies were ignored.

After removal of those 9 out of fit companies, the distributions of the assets expected return in the return-standard deviation space are depicted in Fig. 3.

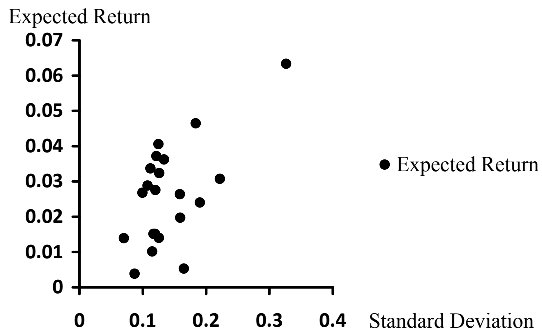

Fig. 3. Distributions of the assets expected return in the return-standard deviation for data.

B. Algorithm Implementation

Proposed algorithm was programmed using *MATLAB* software. After several experiments, the numerical parameters have been determined as following:

Ants number: 168

$Q = 0.1$

evaporation rate or γ : 0.01

repeat count: 500 times

Coefficient vector is suggested as c=[0,1,0,2,0,3,0,4]. This ensures equal choice for stocks of being excluded and/or included as portfolio members.

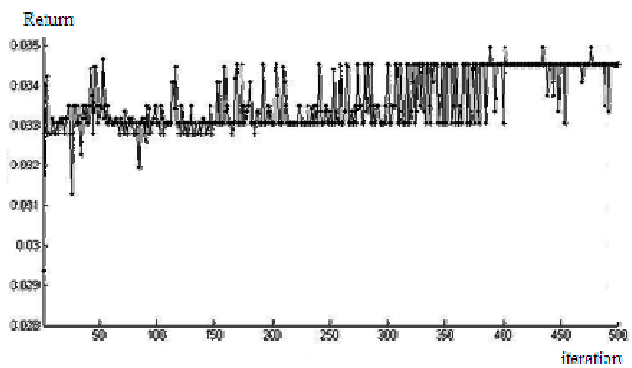

Fig. 4. Return of optimal portfolio for each iteration.

Fig.4 and Fig.5 show the performance of proposed algorithm on objective functions.

As Fig.4 shows return of optimum portfolio, increases as a whole in a converging trend.

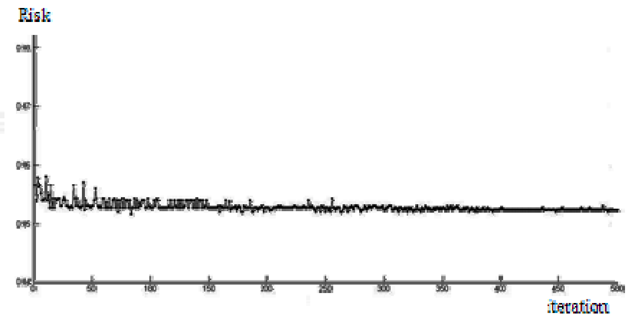

Fig. 5. Risk of optimal portfolio for each iteration.

As Fig.5 shows risk of optimum portfolio, decreases as a whole in a converging trend.

To evaluate the reliability, algorithm was run 30 times. Table.VII (Appendix) presents the results of algorithm run for 30 times. Distribution graph of the results is plotted as Fig.6.

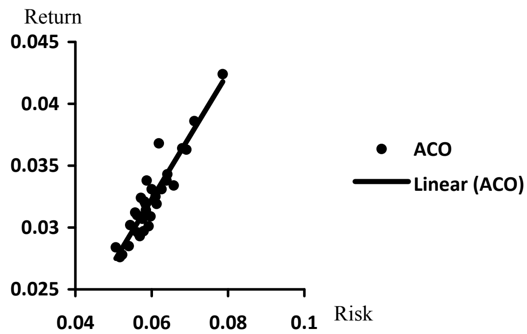

Fig. 6. Distributions of results for ant colony optimization algorithm.

Correlation coefficient of scattered points on the graph was calculated by correlation coefficient analysis. Reliability of proposed algorithm is confirmed by score of 93% for correlation coefficient.

In order to compare the performance of ACO algorithm with an exact method, efficient frontier line is drawn using the *frontcon* function of *MATLAB* software. As Fig.7 shows the results of ACO points, are located under the efficient frontier of *frontcon* function. In other words, performance of *frontcon* function is preferred to ACO approach.

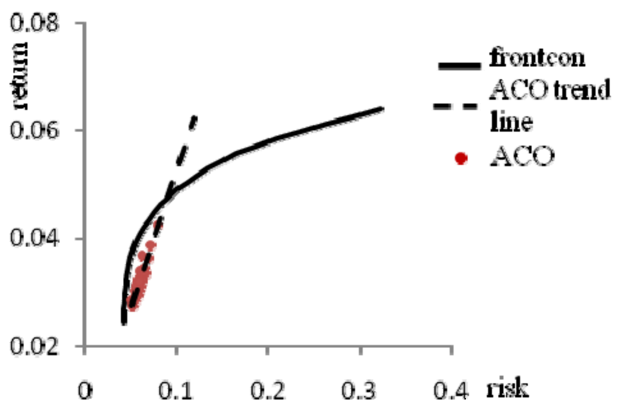

Fig. 7. Comparing exact method with ACO approach.

To ensure that there is significant difference between the results obtained by ACO approach and exact method, *Wilcoxon Signed-Rank Test* was performed. The *Wilcoxon Signed-Rank Test*, compare two sets of scores that come from the same participants. Results of ACO approach and *frontcon* function implementation were paired with risk amount as Table.VIII (Appendix) presents. The distribution of the differences between the scores of the two related groups, were tested for normality. Because of abnormally distribution, *Wilcoxon Signed-Rank Test* was used as a nonparametric test. Table.III points to test result.

TABLE.III: WILCOXON SIGNED-RANK TEST

	frontcon-ACO
Z	-4.783
Asymp. Sig. (2-tailed)	0.000

As *Wilcoxon Signed Ranks Test* shows that there is significant difference between the results obtained by ACO approach and exact method.

As an attempt to improve the algorithm performance, after 30 runs of algorithm the results are considered. This consideration reveals that %10 of results, are identical in returns, while differing in risks. So regarding this fact, it seems that yet there is more opportunity to further improve the risk optimization through more investigation of outcomes.

Then, the optimal risk values are calculated by *Lingo* software for each return value of ACO implementation. Fig.8 presents the distribution graph of the risk values of ACO and *Lingo* in a comparison. After allocating of least risks to ACO identical results, a further comparison is made with *Lingo* ones, which reveals a resemblance in the outcomes.

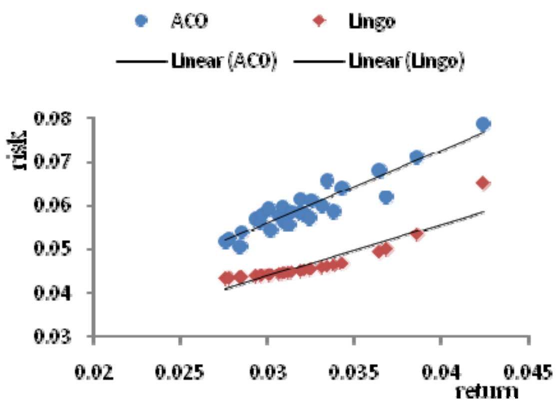

Fig. 8. Distribution graph of the risk values of ACO and Lingo.

As it can be interpreted from Fig.8, the results of *Lingo* points are located below the ACO points. Implying the risk value calculated by *Lingo* is more optimal than ACO. Correlation coefficients of scattered points for both point sets are calculated by *Pearson Correlation Coefficient* analysis. Table IV points to test result.

TABLE.IV: PEARSON CORRELATION COEFFICIENT ANALYSIS

	ACO	Lingo
Pearson Correlation Coefficient	%93	%90.8
sig	0.000	0.000

Pearson Correlation Coefficient analysis confirmed that results are correlated and aligned. ACO align with *Lingo* is a further support for ACO approach reliability.

To ensure that there is significant difference between the risk values obtained by ACO and *Lingo* software, *Paired Sample T-Test* was performed. Risk value of ACO approach and *Lingo* software implementation were paired with return amount as Table.IX (Appendix) presents. The distribution of the differences between the scores of the two related groups, were tested for normality. Regarding to the type of variables and normality of distribution, *Paired Sample T-Test* was used. Table.IV points to test result.

TABLE.IV: PAIRED SAMPLE T-TEST

t	sig
22.832	0.000

As *Paired Sample T-Test* shows that there is significant difference between the risk values obtained by ACO and *Lingo*.

VI. CONCLUSION

Nowadays, studies on ACO approach are extending in several fields of finance, like banking, ecommerce, marketing, risk management and etc. Following the pheromone trail and exploring the shortest path is interpreted as reflections effectiveness and efficiency in biological life. It can be inferred as the potential ability of ACO to be used in finance.

In present study, an ACO algorithm was proposed for POP. This algorithm, search the solution space using ants for optimum rate of return on risk. Algorithm is performed in three major steps, coefficient allocation, quality assessing, and updating.

Convergence of the algorithm results regarding objective functions is a good feature. Despite the stochastic condition of Ant Colony Algorithm, its reliability is proved at a high level.

The results confirmed the preferred outcomes of *frontcon* function as an exact method with significant difference.

Further more in an attempt to improve the algorithm performance, risk values obtained by ACO approach, were compared with *Lingo* optimal results.

ACO accompanied with *Lingo* provide further support for ACO approach reliability. The results confirmed a significant difference between the risk values of ACO and *Lingo* optimal ones. It means that yet more attempts are needed to improve the ACO algorithm toward a more applicable one.

Attempts could be directed towards emphasize on the process of risk optimization of proposed ACO algorithm.

APPENDIX

TABLE.VI: RESULTS OF ACO APPROACH FOR 30 TIMES IMPLEMENTATIONS

Company Number	Expected Return	Company Number	Expected Return
1	0.02637072	13	0.024033696
2	0.005313055	14	0.003862015
3	-0.001537419	15	0.036241439
4	0.026791422	16	0.032354138
5	0.037195576	17	0.019717144

6	-0.010336788	18	0.013989556
7	0.015143413	19	-0.003653231
8	0.040557961	20	0.033686299
9	0.015156778	21	0.030742264
10	0.063340765	22	0.028829229
11	0.046469467	23	0.013909435
12	0.010165571	24	0.027550934

TABLE.VII: RESULTS OF ACO APPROACH FOR 30 TIMES IMPLEMENTATIONS

Portfolio Number	risk	return	Portfolio Number	risk	return
1	0.0597	0.0309	16	0.0639	0.0338
2	0.0572	0.0324	17	0.0619	0.0368
3	0.0587	0.0338	18	0.0581	0.0321
4	0.0562	0.031	19	0.068	0.0364
5	0.0576	0.0307	20	0.0585	0.0314
6	0.0626	0.0331	21	0.0712	0.0386
7	0.0613	0.0319	22	0.054	0.0285
8	0.0592	0.0301	23	0.0691	0.0363
9	0.0506	0.0284	24	0.0557	0.0312
10	0.061	0.0325	25	0.0584	0.0319
11	0.0579	0.0297	26	0.0563	0.0296
12	0.0569	0.0293	27	0.0523	0.0278
13	0.0517	0.0276	28	0.0544	0.0302
14	0.06	0.0331	29	0.0786	0.0424
15	0.0658	0.0334	30	0.0641	0.0343

TABLE.VIII: RESULTS OF ACO AND FRONTCON FUNCTION PAIRED WITH RISK

Risk	ACO	*frontcon*	risk	ACO	*frontcon*
0.0506	0.0284	0.0371	0.0587	0.0338	0.0405
0.0517	0.0276	0.0377	0.0592	0.0301	0.0407
0.0523	0.0278	0.038	0.0597	0.0309	0.0409
0.054	0.0285	0.0388	0.06	0.0331	0.0409
0.0544	0.0302	0.039	0.061	0.0325	0.04124
0.0557	0.0312	0.0395	0.0613	0.0319	0.0413
0.0562	0.031	0.0397	0.0619	0.0368	0.0415
0.0563	0.0296	0.03972	0.0626	0.0331	0.0417
0.0569	0.0293	0.0399	0.0639	0.0338	0.042
0.0572	0.0324	0.04	0.0641	0.0343	0.0421
0.0576	0.0307	0.0402	0.0658	0.0334	0.04254
0.0579	0.0297	0.0403	0.068	0.0364	0.0428
0.0581	0.0321	0.0403	0.0691	0.0363	0.0434
0.0584	0.0319	0.0404	0.0712	0.0386	0.0439
0.0585	0.0314	0.0405	0.0786	0.0424	0.0454

TABLE.IX: RISK VALUES OF ACO AND LINGO, PAIRED BY RETURN VALUES

Return	ACO	*Lingo*	Return	ACO	*Lingo*
0.0276	0.0517	0.0432	0.0319	0.0584	0.0451
0.0278	0.0523	0.0433	0.0319	0.0613	0.0451
0.0284	0.0506	0.0435	0.0321	0.0581	0.0452
0.0285	0.054	0.0435	0.0324	0.0572	0.0453
0.0293	0.0569	0.0438	0.0325	0.061	0.0454
0.0296	0.0563	0.0439	0.0331	0.06	0.0458
0.0297	0.0579	0.0440	0.0334	0.0658	0.0460
0.0301	0.0592	0.0441	0.0338	0.0587	0.0463
0.0302	0.0544	0.0442	0.0343	0.0641	0.0468
0.0307	0.0576	0.0444	0.0364	0.068	0.0494
0.0309	0.0597	0.0445	0.0368	0.0619	0.0501
0.031	0.0562	0.0446	0.0386	0.0712	0.0535
0.0312	0.0557	0.0447	0.0424	0.0786	0.0653

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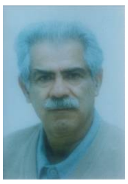

Kambiz Forqandoost Haqiqi was born on November 1947 in Tehran, Iran. His B.A degree is in Auditing from Advanced Institute of Accounting, Tehran, Iran in 1971. He earned his M.B.A from Iran Center for Management Studies, Tehran, Iran in 1976, and PhD degree in Management emphasize on Financial Accounting from Science and Research Branch of Iran Islamic Azad University, Tehran, Iran in 1994. Now He is a member of faculty, Economics & Accounting, Iran Islamic Azad University, Central Tehran Branch, Tehran, Iran. Hi is a member of the Association of Iranian Public Accountants. He is interested in the following research topics: IT Audit, Accounting Origins in Orient, and Accounting History.

Tohid Kazemi was born on 23 July 1986 in Urmia, Iran. His B.A degree is in Accounting from Urmia University, Iran in 2008. Consecutively, he earned his Master degree in Accounting from the Iran Islamic Azad University, Central Tehran Branch, Tehran, Iran in 2011, and now he is PhD student of Accounting from Faculty of Economics and Social Science, Shahid Chamran University of Ahvaz, Ahvaz, Iran. He is a member of Iranian Accounting Association and International Economics Development Research Center. He is interested in the following research topics: Artificial Intelligence in Finance and Accounting, and Behavioral Accounting Research.