The University of Tehran Press

Interdisciplinary Journal of Management Studies (IJMS)
Home Page: https://ijms.ut.ac.ir

Online ISSN: 2981-0795

Predicting Auditor Opinion by a new Metaheuristic Algorithm: Water Cycle Algorithm

Mohammad Moradi[1] | Hoda Eskandar[2*] | Hassan Yazdifar[3] | Aziz Seyedi[4] | Hadi Eskandar[5]

1. Department of Accounting, College of Management, University of Tehran, Tehran, Iran. E-mail: moradimt@ut.ac.ir
2. Corresponding Author, Department of Accounting, Faculty of Management and Accounting, Allameh Tabataba'i University, Tehran, Iran, Tehran, Iran. E-mail: heskandar@atu.ac.ir
3. Department of Accounting, College of Business, University of Derby, Derby, UK. E-mail: H.Yazdifar@derby.ac.uk
4. Department of Accounting, College of Management, University of Tehran, Tehran, Iran. E-mail: saccounting1980@yahoo.com
5. Department of Mechanical Engineering, University of Semnan, Semnan, Iran. E-mail: hadi.eskandar@yahoo.com

ARTICLE INFO

Article type:
Research Article

Article History:
Received 19 July 2023
Revised 07 December 2023
Accepted 07 December 2023
Published Online 18 September 2024

Keywords:
Audit Opinion, Water Cycle Algorithm, Logistic Regression.

ABSTRACT

An auditor evaluates whether financial statements which the firms issue in public, present a fair view. The audit report is a formal letter containing independent verification of the quality of financial statements used for making economic decisions. Hence, the issuance of such a report offers pertinent details about the firm and enhances confidence degree in the financial statements. This study predicts audit opinion of the firms listed on the Tehran Stock Exchange (TSE) during 2018-2020 using a new metaheuristic algorithm named Water Cycle Algorithm (WCA) and compares its results with one of the most popular methods called logistic regression (LG). 24 variables were extracted from the literature and used for this prediction. Four evaluating criteria were used to compare the predictions of the two methods. According to the findings, the superiority of the criteria in the WCA was confirmed in comparison with LG. Since WCA was more appropriate, users of financial reports can use it to predict audit opinions in interim statements. Auditors can also utilize it for evaluating and accepting clients, thereby achieving an acceptable level of audit risk, as a quality control tool.

Cite this article: Moradi, M.; Eskandar, H.; Yazdifar, H.; Seyedi, A. & Eskandar, H. (2024). Predicting Auditor Opinion by a new Metaheuristic Algorithm: Water Cycle Algorithm. *Interdisciplinary Journal of Management Studies* (*IJMS*), 17 (4), 1189-1202. DOI: http//doi.org/10.22059/ijms.2023.362553.676054

Publisher: University of Tehran Press.
DOI: http//doi.org/10.22059/ijms.2023.362553.676054

Introduction

Firms issue financial statements preparing some information about their position and performance. So, stakeholders use this information while making decisions. Therefore, the reliability of such statements and information is a vital issue because if not prepared accurately, users are highly likely to make inappropriate decisions. Increasing the confidence in such statements requires an independent party (auditor) to judge if this information is prepared fairly or not. In other words, the auditor verifies that the financial reports and records offer an accurate picture of the company, and audited financial statements can be considered as reliable sources of information because the opinion of an independent party, adds to the reliability of these statements. In these cases, the users feel free about making decision based on the statements (Karami, Karimiyan, & Salati, 2017).

The report, issued by an auditor, is a formal document, including the audit opinion on financial statements. Audit opinions are divided into two general classes: unqualified opinion and qualified one. The unqualified opinion is reported when the auditor does not detect any material misstatements in the statements. However, the latter shows the existance of such misstatements, detected by the auditor (Sánchez-Serrano, et al., 2020).

Predicting audit opinion is a helpful tool which gives a helping hand to audit firms, aiming to make some decisions such as assessing audit risk, accepting clients and determining audit fee based on their risk (Sánchez-Serrano et al., 2020). Hence, recently, researchers have shown strong tendency to do some research, hoping to predict audit opinion type. Some researchers have developed models which contribute to the prediction of such opinions. Prior researches have used different methodologies in their search to develop a better model, preparing them with more accurate predictions. One of the most popular methods to predict binary variables (variables with only two values) is logistic regression (LG) (e.g., Moalla et al., 2017, Yasar, Yakut, & Gutnu, 2015, Spathis, Doumpos, & Zopounidis, 2003, Laitinen and Laitinen, 1998).

This study seeks to predict audit opinion by some variables extracted from the literature and at last, evaluate the efficiency of such a prediction. The purpose of this study is to predict audit opinion by a new metaheuristic algorithm named water cycle algorithm (WCA) and compare its results with one of the most popular methods named logistic algorithm (LG).

Literature Review

As it was mentioned before, recently some researchers have tried to predict audit opinion and so, there are a few papers related to such prediction. The auditors play a dual role in this process: an informative role and a role for information security and reliability. The auditor as an independent party, verifies the financial statements (DeAngelo, 1981).

To predict the audit opinion, prior researches used different methodologies to devise a model to predict better. Early scholars usually use statistical analysis methods to study audit risk early warning of companies. One of the most popular of such methods is logistic algorithm (LG).

Laitinen and Laitinen (1998) applied a logistic model based on investigated financial ratios to determine the audit opinion. They analysed 37 firms listed on the Helsinki Stock Exchange using 17 explanatory variables. They confirmed that qualified opinions are correlated with low profitability, low growth, and high indebtedness. Of course, the accuracy of their method was 62%. Spathis, Doumpos, and Zopounidis (2003) and Moalla, et al., (2017) used some financial, non-financial and economic variables and applied LG to predict audit opinion among 100 Greek firms. According to their results, some variables like collection/sales, sales/total assets, net profit/total assets, and working capital/total assets enjoy the most predictive power. Saaydah (2019) and Susanto and Pradipta (2017) found a relationship between corporate governance mechanisms and audit opinion by LG. Similarly, Dopuch, Holthausen, and Leftwich (1987) found predictors of audit opinions by using some market and financial variables.

Other authors have utilized other methods in such a prediction and have found the following evidence:

Yasar, Yakut, and Gutnu (2015) utilized discriminant analysis, logit, and decision trees to predict audit opinions among a set of firms listed on Istanbul Stock Exchange. They found that some ratios such as profitability and debt are strong predictors of audit opinion.

Pourheydari and Azami (2011) predicted audit opinion using a neural networks approach during 2003 to 2009. The input variables were composed of a set of financial and non-financial ones such as financial distress and firm litigation respectively.

Setayesh, et al. (2015) forecasted audit opinions by data mining during 2001 to 2010. Predictive variables included liquidity, profitability, leverage, efficiency, size and cash flow.

Heng-Shu (2017) used some financial indicators as predictive variables and developed a fuzzy neural network to predict audit opinions.

Sánchez-Serrano, et al. (2020) predicted audit opinion in consolidated financial statements by artificial neural networks. They found that besides some financial ratios (current and quick ratio, operating and investing cash flow), size, auditor, and board members were the main predictive variables.

Zeng, Li and Li (2022) predicted audit opinion by Sparse Principal Component Analysis and Kernel Fuzzy Clustering Algorithm.

Since traditional methods are limited by strict assumptions and have poor fault tolerance, other methods especially metaheuristic ones are used. Recently, metaheuristic algorithms, especially one of the new ones called water cycle algorithm (WCA), has been proved effective in tackling financial problems (Moradi, et al., 2017). WCA is based on water cycle process in nature (Eskandar et al., 2012). At first, it was introduced by Eskandar et al. (2012) for solving engineering optimization issues. Recently, Moradi et al. (2017) have used this method in the financial field. They utilized it for optimizing portfolio selection. Their findings showed that this method is more efficient than genetic algorithm and particular swarm algorithm.

Since the efficiency of such an algorithm has been approved in solving engineering problems and the portfolio selection problem, this study aims to examine its application in predicting audit opinion in comparison with LG.

According to the above, the hyposeses are as the following:

1. “WCA is appropriate for predicting audit opinion.”
2. “WCA is more efficient than LG regression in predicting audit opinion.”

Methodology

The population consists of all of the firms listed on the TSE. The sample was also selected through a systematic removal method from the statistical population with considering the following criteria:

Firms listed on TSE from 2018 to 2020 were included while financial firms and those with inaccessibledata were excluded.

At last, the sample includes 237 firms during 3 years (711 observations). We collected their data from annual reports and TSE reports obtained from electronic data and the Internet.

The dependent variable of this study is audit opinion. It is a dummy variable that is 1 when audit opinion issues an unqualified report and otherwise, it is 0. Moreover, independent variables include 24 explanatory variables (recognized based on prior literature). They are shown in the following table:

Table 1. Research Variables

Title	Variable	Measurement	Symbol	Reference
Liqidity	Current Ratio	Current assets/current liabilities	x1	Sánchez-Serrano, et al. (2020) Pourheydari and Azami (2011)
	Quick Ratio	Current assets (excluding inventory and prepaids)/ current liabilities	x2	
Asset management	Inventory Turnover	Net sale/inventory average	x3	Heng-Shu (2017) Pourheydari and Azami (2011)
	Asset Turnover	Net sale/ assets average	x4	Spathis, Doumpos, and Zopounidis (2003) Pourheydari and Azami (2011)
	Receivables Turnover	Net sale/ receivables average	x5	Heng-Shu (2017) Pourheydari and Azami (2011)

Table 1.

Title	Variable	Measurement	Symbol	Reference
profitability	Return on Asset	Net income/assets	x6	Yasar, Yakut, and Gutnu, (2015) Laitinen and Laitinen (1998) Pourheydari and Azami (2011)
	Return on Investment	Net income / investment	x7	
	Return on Shareholders Equity	Net income/ stockholders' equity	x8	
	Net Income Ratio	Net income/ sale	x9	
Cash flows	Operating Cash ratio	Operating cash flow/sale	x10	Sánchez-Serrano, et al. (2020) Pourheydari and Azami (2011)
	Investing Cash Ratio	Investing cash flow/sale	x11	
Debt management	Debt Ratio	Liabilities/ assets	x12	Yasar, Yakut, Gutnu, and (2015) Laitinen and Laitinen (1998) Pourheydari and Azami (2011)
Market value	Market to Book Value	Market value/book value	x13	Dopuch, Holthausen, and Leftwich (1987)
stock	Stock Return	Dividend/ stock price	x14	
	Price to Revenue	Stock price/ EPS	x15	
growth	Firm Growth	(Assetst-Assets$_{t-1}$)/Assets $_{t-1}$	x16	Laitinen and Laitinen (1998) Setayesh, et al. (2015)
size	Log Net Sales	Log net sale	x17	
Corporate governance	Audit Firm Type	If audit organization is the firm auditor, 1 otherwise 0	x18	Saaydah (2019) Susanto and Pradipta (2017) Sánchez-Serrano, et al. (2020)
	Prior AuditOpinion	If prior audit opinion is unqualified 1, otherwise 0	x19	
	Auditor Switch	If auditor switched to audit organization or the reverse, 1 otherwise 0	x20	
	Management Switch	If CEO of the members of director board are switched 1, otherwise 0	x21	
	Auditor Tenure	If auditor is not switched during 2 period 1, otherwise 0	x22	
	Nomber of Board of Directors Members	Log the number of director board	x23	
others	Firm Age	Firm age	x24	Zeng, Li, and Li (2022) Setayesh, et al. (2015)

In this study, variables are computed by Excel, and WCA is run by Matlab software.

WCA

The WCA emulates the flow of rivers and streams towards the sea, inspired by the observation of the water cycle process. Assuming precipitation events, an initial population of design variables (streams) is randomly generated after the rainfall process. The sea is determined as the best individual with the minimum cost function (for minimization problems), while other good streams (close to the current best record) are designated as rivers. The remaining streams flow into the rivers and the sea. In a D-dimensional optimization problem, a stream is represented as a 1×D array in an initial population matrix of size N_{pop}×D.

:

$$Total \quad Population = \begin{bmatrix} Sea \\ River_1 \\ River_2 \\ River_3 \\ \vdots \\ Stream_{Nsr+1} \\ Stream_{Nsr+2} \\ Stream_{Nsr+3} \\ \vdots \\ Stream_{N_{pop}} \end{bmatrix} = \begin{bmatrix} x_1^1 & x_2^1 & x_3^1 & \cdots & x_D^1 \\ x_1^2 & x_2^2 & x_3^2 & \cdots & x_D^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_1^{N_{pop}} & x_2^{N_{pop}} & x_3^{N_{pop}} & \cdots & x_D^{N_{pop}} \end{bmatrix},$$

N_{pop}: population size, *D:* design variables number.

Each decision variable (x1, x2, ..., xD) can take on real values or predefined sets depending on whether the problem is continuous or discrete, . The stream's cost is obtained by evaluating the cost function. Initially, N_{pop} streams are created, and Nsr of the best individuals are selected as rivers and one as the sea.

Depending on the flow magnitude, rivers absorb water from streams, and the amount of water entering a river or the sea varies. The following equation alludes to calculate the designated streams for each river and sea (Eskandar et al., 2012):

$$C_n = Cost_n - Cost_{Nsr+1} \qquad n = 1, 2, 3, ..., N_{sr} \ ,$$

$$NS_n = round\{\left| \frac{C_n}{\sum_{n=1}^{N_{sr}} C_n} \right| \times N_{Streams}\} \quad , \quad n = 1, 2, ..., N_{sr} \ ,$$

NS_n: number of streams which flow to the specific rivers and sea.

Streams are generated from raindrops, joining to form new rivers, and some may flow directly to the sea. All rivers and streams converge into the sea, representing the current best solution.

During the exploitation step, new positions for streams and rivers are suggested. If a stream's solution is better than its connecting river, their positions are exchanged. A similar exchange can occur between a river and the sea (Eskandar et al., 2012):

$$\vec{X}_{Stream}^{t+1} = \vec{X}_{Stream}^{t} + rand \times C \times (\vec{X}_{Sea}^{t} - \vec{X}_{Stream}^{t}) \qquad \vec{X}_{Stream}^{t+1} = \vec{X}_{Stream}^{t} + rand \times C \times (\vec{X}_{River}^{t} - \vec{X}_{Stream}^{t})$$

$$\vec{X}_{River}^{t+1} = \vec{X}_{River}^{t} + rand \times C \times (\vec{X}_{Sea}^{t} - \vec{X}_{River}^{t})$$

$1 < C < 2$ and the optimal value for C may be chosen as 2 and *rand* is a uniformly distributed random number between zero and one.

These equations are for streams flowing into the sea and their corresponding rivers, respectively. Notations having vector sign correspond to vector values: in contrast, the rest of the notations and parameters are considered as scalar values. If the solution given by a stream is better than its connecting river, the positions of the river and stream are exchanged (i.e., the stream becomes a river and the river becomes a stream).

To prevent premature convergence to local optima, an evaporation process is introduced. Evaporation occurs as sea water evaporates from rivers/streams flowing into the sea, leading to new precipitations. A criterion is used to check if the river/stream is sufficiently close to the sea for the evaporation process (Eskandar et al., 2012):

$$\begin{array}{l} if \ \left\| \vec{X}_{Sea}^{t} - \vec{X}_{River_j}^{t} \right\| < d_{\max} \quad or \quad rand < 0.1 \qquad j = 1, 2, 3, ..., N_{sr} - 1 \\ \quad Perform \ \ raining \ \ process \ \ by \ \ unifrom \ \ random \ \ search \ , \\ end \end{array}$$

d_{max}: a small number close to zero.

After evaporation, a rainfall process occurs, creating new streams. The best stream in the new subpopulation becomes a new river, and other streams move toward their new rivers. This condition applies to streams directly flowing into the sea.

The best newly formed stream is considered a river flowing to the sea, while the rest may flow into rivers or directly into the sea. An equation encourages the creation of streams directly flowing to the sea to enhance exploration near the sea, optimizing solutions for constrained problems (Eskandar et al., 2012):

$$\overset{\mathbf{\scriptscriptstyle 1}}{X}{}^{t+1}_{Stream} = \overset{\mathbf{\scriptscriptstyle 1}}{X}{}^{t}_{Sea} + \sqrt{\mu} \times randn\,(1, D)$$

μ: a coefficient illustrating searching region range near the sea, *randn*: normally distributed random number. The larger μ is highly likely to exit from feasible era. Its suitable value is set to 0.1. In fact, the term $\sqrt{\mu}$ represents the standard deviation. The generated individuals with variance μ are distributed around the sea.

As a result, the evaporation operator is responsible for the exploration phase.

A large value for d_{max} prevents extra searches and small values motivate the search intensity near the sea. The value of d_{max} adaptively falls as follows:

$$d^{t+1}_{\max} = d^{t}_{\max} - \frac{d^{t}_{\max}}{Max\_Iteration} \qquad t = 1, 2, 3, \ldots, Max.\ \ Iteration$$

T: an iteration index.

To sum up, WCA includes the following steps (Sadollah et al., 2015):

S1: Determine the parameters: N_{sr}, d_{max}, N_{pop}, maximum iteration number, and Pareto archive size.

S2: Form a random initial population, streams, rivers, and the sea.

S3: Evaluate functions interms of each stream.

S4: Determine the non-dominated solutions in the initial population and the feasible solutions and save them in the Pareto archive.

S5: Calculate the crowding-distance for each Pareto archive member.

S6: Choose a sea and its corresponding rivers, and determine flow intensity of both rivers and the sea (some streams may directly flow into the sea).

S7: Exchange positions of the sea with a stream which gives the best solution.

S8: Streams flow into the rivers.

S9: Repeat S 7 interms of river instead of the sea.

S10: River's flow into the sea.

S11: Exchange positions of the sea with a river giving the best solution.

S12: Check the evaporation condition by the pseudo-code.

S13: The raining process will take place if the evaporation condition is satisfied.

S14: Decrease d_{max} being a user defined parameter.

S15: Identify the new solutions in the population which are feasible.

S16: Identity the new non-dominated solutions among the feasible solutions and save them in the Pareto archive.

S17: Remove any dominated solutions in the archive.

S18: Go to S 17 if the member number in the archive is more than the determined archive sizes, otherwise, go to the S 20.

S19: Valuate the crowding-distance for each Pareto archive member and eliminate as many members as necessary. Those members which have the lowest crowding-distance value must be remited.

S20: Repeat the prior steps to select a new sea and rivers.

S21: Consider the convergence criterion. The WCA stops if the stopping criterion is satisfied; otherwise, return to S9.

Table 2 provides the pseudocode of WCA algorithm.

Table 2. Pseudo-code of the WCA

```
• Set parameter: N_pop, N_sr, and the maximum number of iterations.
• Recognize the number of streams flowing to the rivers and the sea.
• Randomly generate initial population in upper and lower bounds of a given problem.
• Choose the sea, rivers, and streams.
• Define the intensity of flow
while (t ≤ Maximum_Iteration) or (any defined stopping condition)
    for i = 1: Population Size (N_pop)
        Streams directly flow to the sea
        Calculate the objective function of the generated stream
            if Cost (New_Stream) < Cost (Sea)
                Sea = New_Stream;
            end if
        Streams flow to their corresponding rivers using
        Calculate the objective function of the generated stream
            if Cost (New_Stream) < Cost (River)
                River = New_Stream;
                    if Cost (New_Stream) < Cost (Sea)
                        Sea = New_Stream;
                    end if
            end if
        Rivers flow to the sea
        Calculate the objective function of the generated river
            if Cost (New_River) < Cost (Sea)
                Sea = New_River;
            end if
    Check the evaporation condition
end while
Post process results and visualization
```

Logistic Regression (LG)

logistic model is a statistical regression, modeling the probability of an event occurring by having the log-odds for the event be a linear combination of one or more independent variables. In binary logistic regression, there is a dependent variable, coded by two values: either "0" or "1". The corresponding probability of the value labeled "1" can vary between 0 (indicating the value "0") and 1 (indicating the value "1"), hence the labeling; the function that converts log-odds to probability is the logistic function, hence giving the model its name. The unit of measurement for the log-odds scale is called a *logit*, from *logistic unit*, hence explaining the alternative terminology. See § Background and § Definition for formal mathematics, and § Example for a worked example.

LG is one of the most popular and commonly used methods in forcasting the events in different fields such as eangineering, medicine, and social science.

Evaluating Criteria

In evaluating the results of the methods, the real outcomesare compared with the predicted outcome as shown in the following table. This table represents a confusion matrix:

Table 3. Confusion Matrix

	Prediction group			
	Negative	positive		
Sensitivity $\frac{TP}{(TP + FN)}$	False Negative (FN) β error	True Positive (TP)	positive	Real group
Specifity $\frac{TN}{(TN + FP)}$	(TN) True Negative	False Positive (FP) α error	negative	
Accuracy $\frac{TP+TN}{(TP+TN+FP+FN)}$	Negative Prediction Value $\frac{TN}{(TN + FN)}$	Percision $\frac{TP}{(TP + FP)}$		

To assess how well a model predicts a binary outcome, four popular criteria are commonly used.

Accuracy refers to the proportion of individuals correctly classified. In other words, accuracy means that how well the model predicts the output (audit opinion). Precision means that when the model predicts a positive outcome, how much this outcome can be correct and appropriate. Sensitivity is the rate of accurate positive outcome and specificity is the rate of accurate negative outcome.

Fig. 1 demonstrates the study steps:

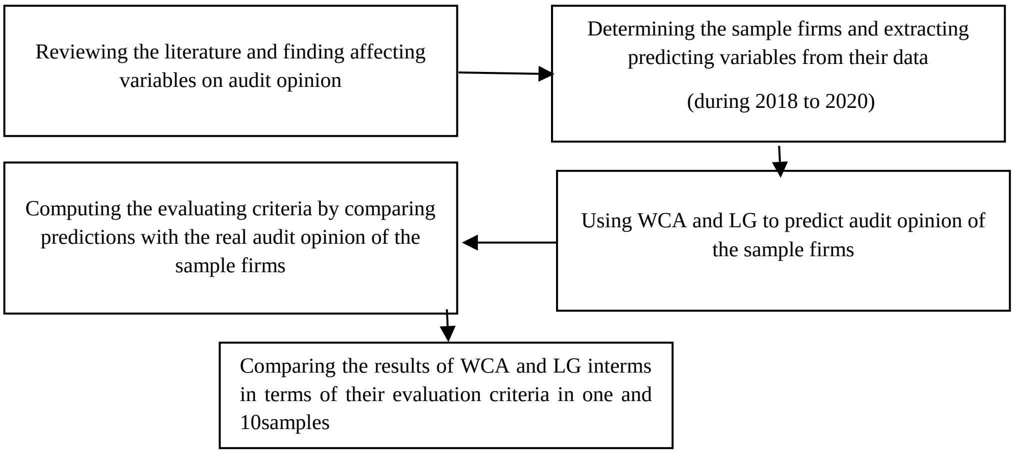

Fig. 1. The steps of the study

Results

Descriptive Statics

Table 4 demonstrates the descriptive statistics of research variables.

Table 4. Descriptive Statistics

Variable	Symbol	Max	Min	Mean	S.D
Current Ratio	x1	6.17	0.39	1.53	1.01
Quick Ratio	x2	5.55	0.18	1.01	0.78
Inventory Turnover	x3	1730.70	3.09	167.38	210.72
Asset Turnover	x4	3.97	0.05	0.87	0.63
Receivables Turnover	x5	27.06	0.02	4.34	4.26
Return on Asset	x6	421.62	-41.37	35.64	72.05
Return on Investment	x7	326.83	-57.11	45.03	62.52
Return on Shareholders Equity	x8	70.55	-46.90	19.88	22.26
Net Income Ratio	x9	87.66	-33.15	9.03	17.59
Operating Cash ratio	x10	1.57	-5.35	0.06	0.34
Investing Cash Ratio	x11	0.14	-.069	-0.07	0.12
Debt Ratio	x12	1.13	0.13	0.57	0.20
Market to Book Value	x13	61.39	1.01	7.77	9.99
Stock Return	x14	0.24	-0.33	0.05	0.08
Price to Revenue	x15	2105.45	-33.08	67.40	234.51
Firm Growth	x16	3.51	-0.20	0.19	0.47
Log Net Sales	x17	8.23	3.98	6.24	0.76
Audit Firm Type	x18	1.00	0.00	0.18	0.38
Prior Audit Opinion	x19	1.00	0.00	0.48	0.50
Auditor Switch	x20	1.00	0.00	0.25	0.43
Management Switch	x21	1.00	0.00	0.33	0.47
Auditor Tenure	x22	1.00	0.00	0.58	0.49
Nomber of Board of Directors Members	x23	0.85	0.48	0.70	0.02
Firm Age	x24	68.94	10.79	40.68	14.35

According to Table 5, by using WCA, 711 observations (years-firms) are classified in 4 models (R1 to R4).

In model R1, prior audit opinion has changed from maximum and minimum initial ranges and and is recognized as the only independent variable; other variables are not considered independent. In model R2, inventory turnover, asset turnover, return on investment, net income ratio, stock return, prior audit opinion and the number of the board of directors have changed and they are also recognized as independent variable. If these variables are within the ranges of (3/09-1100/47), (0/07-3/73), (-6/36-421), (33/15-87/66), (0/24-0/31), (1-1) and (0/70-0/85), it is possible to predict audit opinion with 76% precision and 70% accuracy. Consequently, the number of independent variables in model R3 and R4 are 20 and 19 independent variables and the precision and accuracy of prediction are 28%, 78%, 100% and 78% respectively.

Table 5

Variable	**R4**			**R3**		**R2**		**R1**		**symbol**
	18			**7**		**322**		**364**		**No**
Current Ratio	1.70	0.39		2.59	0.51	6.17	0.39	6.17	0.39	x1
Quick Ratio	1.67	0.19		1.67	0.20	5.55	0.18	5.55	0.18	x2
Inventory Turnover	383.53	3.09		383.53	3.09	1100.47	3.09	1730.70	3.09	x3
Asset Turnover	3.97	0.18		3.97	0.18	3.73	0.07	3.97	0.07	x4
Receivables Turnover	27.06	0.63		27.06	0.63	27.06	0.02	27.06	0.02	x5
Return on Asset	31.27	-16.75		40.40	-16.75	46.39	-16.75	46.39	-16.75	x6
Return on Investment	200.75	-46.90		421.62	-30.79	421.62	-6.36	421.62	-57.11	x7
Return on Shareholders Equity	78.76	-37.40		78.76	-37.40	78.76	-37.40	78.76	-37.40	x8
Net Income Ratio	6.19	-33.15		9.88	-33.15	87.66	-33.15	87.66	-46.90	x9
Operating Cash ratio	0.44	-0.12		0.77	-0.12	0.77	-0.31	0.77	-0.31	x10
Investing Cash Ratio	0.00	-0.04		0.09	-0.09	0.14	-0.69	0.14	-0.69	x11
Debt Ratio	1.13	0.22		1.13	0.22	1.13	0.13	1.13	0.13	x12
Market to Book Value	26.18	1.01		42.01	1.01	61.39	1.01	61.39	1.01	x13
Stock Return	0.05	-0.31		0.11	-0.29	0.24	-0.31	0.24	-0.33	x14
Price to Revenue	109.55	-33.08		109.16	-33.08	205.45	-33.08	205.45	-33.08	x15
Firm Growth	1.11	-0.17		3.51	-0.17	3.51	-0.20	3.51	-0.20	x16
Log Net Sales	7.67	4.41		8.23	4.41	8.23	3.98	8.23	3.98	x17
Audit Firm Type	1.00	0.00		1.00	0.00	1.00	0.00	1.00	0.00	x18
Prior Audit Opinion	1.00	1.00		1.00	1.00	1.00	1.00	0.00	0.00	x19
Auditor Switch	1.00	0.00		1.00	0.00	1.00	0.00	1.00	0.00	x20
Management Switch	1.00	0.00		1.00	0.00	1.00	0.00	1.00	0.00	x21
Auditor Tenure	1.00	0.00		1.00	۰/۰۶	1.00	0.00	1.00	0.00	x22
Nomber of Board of Directors Members	0.70	0.70	0.70	0.70	0.70	0.85	0.70	0.85	0.48	x23
Firm Age	67.12	10.84		670.4	10.84	68.94	10.84	68.94	10.84	x24
group	0			1		1		0		
Audit opinion	qualified	Unqualified		qualified	unqualified	qualified	unqualified	qualified	unqualified	
Prediction group	4	14		0	7	78	244	109	255	
Accuracy	0.78			0.28		0.70		0.36		
Percision	0.78			1.00		0.76		0.70		

Based on Table 6, the number of the firms with qualified report which predicted accurately is 244 plus 7 (251 firms). The number of the firms with unqualified report and inaccurate prediction equals 109 plus 4 (113 firms). The number of the firms with qualified report and accuarate prediction equals 255 plus 14 (269 firms). At last, 78 firms with unqualified report predicted inaccurately (78+0). According to tha table, precision, accuracy, sensitivity and specifcity criteria equals 76, 73, 69 and 78 percent, respectively.

Table 6

	Prediction group 0	Prediction group 1		
Sensitivity 0/690	FN 113	TP 251	1	Real group
Specificity 0/775	TN 269	FP 78	0	Real group
Accuracy 0/731	Negative Prediction Value 0/704	Percision 0/763		

In this section, audit opinion is predicted using WCA and GA for 10-times, aimimg to compare the results of these methods. Table 7 shows the results in 10 samples.

Table 7

Specificity	Sensitivity	Precision	Accuracy	FN	TN	FP	TP	Sample
0.749	0.695	0.744	0.722	111	260	87	253	1
0.746	0.692	0.741	0.719	112	259	88	252	2
0.755	0.690	0.747	0.722	113	262	85	251	3
0.738	0.701	0.737	0.719	109	256	91	255	4
0.735	0.701	0.735	0.717	109	255	92	255	5
0.746	0.695	0.742	0.720	111	259	88	253	6
0.744	0.687	0.737	0.714	114	258	89	250	7
0.749	0.692	0.743	0.720	112	260	87	252	8
0.778	0.654	0.756	0.714	126	270	77	238	9
0.735	0.701	0.735	0.717	109	255	92	255	10
0.778	0.701	0.756	0.722			Best		
0.735	0.654	0.735	0.714			Worst		
0.013	0.014	0.006	0.003			SD		
0.748	0.691	0.742	0.718			Mean		

According to the Table 8, current ratio, inventory turnover and prior audit opinion have changed from maximum and minimum initial ranges and are recognized as independent variables, while the others are not recognized as independent variables.

Table 8

Variable	**range**		**Symbol**
Current Ratio	6.17	0.39	x1
Quick Ratio	5.55	0.18	x2
Inventory Turnover	1730.70	3.10	x3
Asset Turnover	3.97	0.05	x4
Receivables Turnover	27.06	0.02	x5
Return on Asset	46.39	-16.75	x6
Return on Investment	421.69	-57.11	x7
Return on Shareholders Equity	78.76	-37.40	x8
Net Income Ratio	87.66	-46.90	x9
Operating Cash Ratio	0.77	-0.31	x10
Investing Cash Ratio	0.14	-0.69	x11
Debt Ratio	1.13	0.13	x12
Market to Book Value	61.39	1.01	x13
Stock Return	0.24	-0.33	x14
Price to Revenue	2105.45	-33.08	x15
Firm Growth	3.51	-0.20	x16
Log Net Sales	8.23	3.98	x17
Audit Firm Type	1.00	0.00	x18
Prior Audit Opinion	1.00	1.00	x19
Auditor Switch	1.00	0.00	x20
Management Switch	1.00	0.00	x21
Auditor Tenure	1.00	0.00	x22
Nomber of Board of Directors Members	0.85	0.48	x23
Firm Age	68.94	10.84	x24

According to Table 9, the number of the firms which received unqualified audit opinion (1) and were predicted accurately is 253. Audit opinion of 111 firms was unqualified (1) but was not predicted accurately (0). The audit opinion of ۲۶۰ firms was qualified (0) and they were predicted accurately. The audit opinion of 87 firms was qualified, However, their prediction was inaccrate.

Precision, accuracy, sentivity and specificity of the final model are 74%, 72%, 69% and 75% respectively. Therefore, if current ratio, inventory turnover and prior audit opinion arewithin the ranges of (0/39-6/17), (3/10, 1730/70) and (1-1), it is possible to predict audit opinion with 72% accracy and 74% precision.

Table 9

Prediction group

	0	1		
Sensitivity 0/695	FN 111	TP 253	1	Real group
Specificity 0/749	TN 260	FP 87	0	
Accuracy 0/722	Negative Prediction Value 0/701	Percision 0/744		

LG Regression Model

The results of applying LG regression for 10-times (10 samples) are shown in Table 10.

Table 10

Specificity	Sensitivity	Precision	Accuracy	FN	TN	FP	TP	sample
0.695	0.706	0.708	0.700	107	241	106	257	1
0.712	0.692	0.716	0.702	112	247	100	252	2
0.709	0.698	0.715	0.703	110	246	101	254	3
0.703	0.692	0.710	0.698	112	244	103	252	4
0.683	0.703	0.699	0.693	108	237	110	256	5
0.697	0.687	0.704	0.692	114	242	105	250	6
0.706	0.687	0.710	0.696	114	245	102	250	7
0.715	0.692	0.718	0.703	112	248	99	252	8
0.697	0.695	0.707	0.696	111	242	105	253	9
0.706	0.690	0.711	0.698	113	245	102	251	10
0.715	0.706	0.718	0.703			best		
0.683	0.687	0.699	0.692			worst		
0.009	0.006	0.006	0.004			SD		
0.702	0.694	0.710	0.698			Mean		

The result of of 10 samples in LG model are shown in Tables 10 and 11. Based on Table 11, only quick ratio, return on assets, stock return and prior audit opinion are recognized as independent variables (p-value<5%). The coefficients of variables are presented in the following table.

Table 11

variable	P-Value	Z	coefficient	Symbol
C	0.822	0.225	0.721	C
Current Ratio	0.148	1.448	0.350	x1
Quick Ratio	0.020	-2.327	-0.702	x2
Inventory Turnover	0.516	-0.649	0.000	x3
Asset Turnover	0.457	0.743	0.174	x4
Receivables Turnover	0.446	-0.762	-0.024	x5
Return on Asset	0.019	2.338	0.054	x6
Return on Investment	0.964	-0.045	0.000	x7
Return on Shareholders Equity	0.252	-1.146	-0.008	x8
Net Income Ratio	0.430	-0.789	-0.007	x9
Operating Cash Ratio	0.835	-0.209	-0.138	x10
Investing Cash Ratio	0.212	-1.249	-1.118	x11
Debt Ratio	0.123	1.543	1.268	x12
Market to Book Value	0.235	1.187	0.012	x13
Stock Return	0.033	2.126	3.496	x14
Price to Revenue	0.783	0.275	0.000	x15
Firm Growth	0.427	-0.795	-0.154	x16
Log Net Sales	0.051	-1.948	-0.292	x17
Audit Firm Type	0.967	0.041	0.010	x18
Prior Audit Opinion	0.000	10.007	1.750	x19
Auditor Switch	0.456	-0.745	-0.207	x20
Management Switch	0.171	1.368	0.256	x21
Auditor Tenure	0.586	0.549	0.138	x22
Nomber of Board of Directors Members	0.803	-0.250	-1.057	x23
Firm Age	0.486	-0.696	-0.004	x24

Table 12 shows that the accuracy of this model is 70%, its precision is 71% and its sensitivity and specifity are 69% and 71% respectively.

Table 12

	Prediction group 0	Prediction group 1		
Sensitivity 0/695	FN 111	TP 253	1	Real group
Specificity 0/712	TN 247	FP 100	0	Real group
Accuracy 0/703	Negative Prediction Value 0/690	Percision 0/717		

Comparing WCA and LG results

According to Table 13, all the criteria in WCA are better than LG. Therefore, in applying these 2 methods in one sample, WCA has more efficient performance.

Table 13

Method	Specificity	Sensitivity	Precision	Accuracy	FN	TN	FP	TP
WCA	0.749	0.695	0.744	0.722	111	260	87	253
LG	0.712	0.695	0.717	0.703	111	247	100	253

For better comparision, the results obtained from the 2 methods are compared in 10 samples. Based on Table 14, the performance of WCA is better than that of GA. The accuracy and Precision criteria are 72 and 76 percent for WCA. The corresponding criteria for LG are 70 and 71. The sentivity of both methods is approximately the same. Hence, the overallperformance of WCA is better than that of LG. The worst criteria of WCA (except sensitivity) are better than those of LG ones. The worst accuracy and precision in WCA are 71 and 74 percent (in comparision with 69 and 70 forLG). The mean of all criteria (except sensitivity) is better in WCA. The sentivity of mthods is approximately the same.

To sum up, similar to 1 run of methods, in the 10 samples, WCA has better performance.

Table14

	Method	Specificity	Sensitivity	Precision	Accuracy
best	WCA	0.778	0.701	0.756	0.722
	LG	0.715	0.706	0.718	0.703
worst	WCA	0.735	0.654	0.735	0.714
	LG	0.683	0.687	0.669	0.692
SD	WCA	0.013	0.014	0.006	0.003
	LG	0.009	0.006	0.006	0.004
Mean	WCA	0.748	0.691	0.742	0.718
	LG	0.702	0.694	0.710	0.698

Conclusion

Audit report has informative content and importance for the users of the firms' financial statement, aiming to make the best economic decisions. This study seeks to predict audit opinion by using a new metaheuristic algorithm called water cycle algorithm (WCA) and comparing its results with one of the most popular algorithms i.e., logistic algorithm (LG).

This study reviewed the literature and selected 24 independent variables in predicting audit opinion of 237 firms listed on the Tehran Stock Exchange during 2018 to 2020. Audit opinion was measured as a binary variable (1 if the audit opinion was unqualified; otherwise it was 0 whichincludes qualified, disclaimer and adverse opinion)s. Predictions obtained by algorithms are compared with the real audit opinion, and then their results were compared based on some evaluating criteria.

Findings showed that the precision, accuracy, sensitivity and specificity of WCA are 76%, 73%, 69% and 78%, respectivity. Therefore, WCA is an appropriate method for predicting audit opinion. Moreover, the criteria obtained from WCA are better than those of LG; in consequence, WCA is more efficient than LG.

According to the findings, among 24 independent variables, extracted from the literature, the most affecting ones included inventory turnover (consistent with Heng-Shu (2017) and Pourheydari and Azami (2011)) and asset turnover (consistent with Spathis, Doumpos, and Zopounidis (2003) and Pourheydari and Azami (2011)), ROI, net income ratio (consistent with Yasar, Yakut, and Gutnu, (2015) and Laitinen and Laitinen (1998) and Pourheydari and Azami (2011)), the number of board of directors' members and prior audit opinion (consistent with Saaydah (2019) and Susanto and Pradipta (2017) and Lu (2020) and Sánchez-Serrano et al. (2020)).

Given the obtained results, this research has some implications. Since there are significant relationships between audit opinion and some variables (inventory and asset turnover, ROI, net income ratio and the number of board of directors' members and prior audit opinion), it is proposed that users should put more emphasis on such variables, hoping to predict audit opinion efficiently.

Moreover, it is proposed that users of interim period financial statements, some of which are not audited, should use WCA for predicting audit opinion on such statements. Moreover, auditors can use this algorithm in developing audit plans and evaluating and making decision about accepting clients. Additionally, it is useful in estimating acceptable audit risk and determining an appropriate audit fee.

At last, it is proposed as a research opportunity to examine other metaheuristic algorithms and use other predicting variables, which were omittedfrom this studyto predictaudit opinion and compare their results with each other.

References

DeAngelo, L. E. (1981). Auditor size and audit quality. *Journal of Accounting and Economics, 3,* 183–199.

Dopuch, N. W., Holthausen R. & Leftwich R. W. (1987). Predicting audit qualifications with financial and market variables. *The Accounting Review*, *62*(3): 431-454.

Eskandar, H., Sadollah, A., Bahreininejad, A., & Hamdi, M. (2012). Water Cycle Algorithm – A novel metaheuristic optimization method for solving constrained engineering optimization problems. *Computers & Structures*, 110-111, 151-166.

Heng-Shu, T. (2017).Audit opinion of listed companies: A Takagi-Sugeno fuzzy neural network-based study. *Journal of Discrete Mathematical Sciences and Cryptography*, *20*(4), 899–912.

Karami, G., Karimiyan, T., Salati, S.. (2017). Auditor tenure, auditor industry expertise, and audit report lag: Evidences of Iran. *Iranian Journal of Management Studies*, *10*(3): 641-666.

Laitinen, E. K., & Laitinen, T. (1998). Qualified audit reports in Finland: Evidence from large companies. *European Accounting Review, 7*(4), 639-653.

Lu, B. (2020). Literature Review of Audit Opinion. *Modern Economy*, *11*, 28-36.

Moalla, H. (2017). Audit report qualification/modification: Impact of financial variables in Tunisia. *Journal of Accounting in Emerging Economies, 7,* 468–485.

Moradi, M., Ali, S., & Eskandar, H. (2017). The application of water cycle algorithm to portfolio selection. *Economic Research-Ekonomska Istraživanja, 30*(1), 1277–1299.

Pourheydari, O. & Azami, Z. (2011). Predicting auditor's opinions: A neural networks approach. *Journal of Accounting Knowledge, 1*(3), 77-97.

Sánchez-Serrano, J. R., Alaminos, D., García-Lagos, F., & Callejón-Gi, A. M. (2020). Predicting audit opinion in consolidated financial statements with artificial neural networks. *Mathematics*, *8*(8), 1288.

Saaydah, M. (2019). Coeporate governance and the modification of audit opinion: A study in the Jordanian market. *International jounal of applied research in management and economics*, *2*(2), 28-46.

Setayesh, M. H., Ebrahimi, F., Seyf, S. M., Sarikhani, M. (2015). Forecasting the type of audit opinions: A data mining approach. *Management Accounting*, *5*(4), 69-82.

Spathis, C., Doumpos, M., & Zopounidis, C. (2003). Using client performance measures to identify pre-engagement factors associated with qualifed audit reports in Greece. *The International Journal of Accounting*, *38*(3), 267–284.

Susanto, Y. K., & Predipta, A. (2017). Coeporate governance and audit decision making. *Corporate ownership & control*, *15*(1-2), 381-386.

Yaşar, A., Yakut, E., & Gutnu, M. M. (2015). Predicting qualified audit opinions using financial ratios: Evidence from the Istanbul Stock Exchange. *International Journal of Business and Social Science, 6*(8), 57- 67.

Zeng, S., Li, Y. & Li, Y. (2022). Research on audit opinion prediction of listed companies based on sparse principal component analysis and kernel fuzzy clustering algorithm. *Mathematical Problems in Engineering, 2022,* 1-13. https://doi.org/10.1155/2022/4053916