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Evidence for the Ability of the Regression Model and Particle Swarm Optimization Algorithm in Predicting Future Cash Flows

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ABSTRACT

This study predicts future cash flows using a regression model and a particle swarm optimization algorithm (PSO). The variables of accruals components and operating cash flows were used, and the data of 137 listed companies on the Tehran Stock Exchange during 2009-2017 were studied. Eviews9 software for the regression model and Matlab13 software for the Particle swarm optimization algorithm was used to test the hypotheses. The results indicate that the regression model's variables and the Particle swarm optimization Algorithm in this study can predict future cash flows. Furthermore, the results of the fitting Particle swarm optimization Algorithm show that a structure with eight hidden neurons is the best model for predicting future cash flows, and the proposed neural network model compared with the regression model has higher prediction accuracy in predicting future cash flows. This study shows that the classification of assets and liabilities provides useful information from future operating cash flows.

Keywords: Accruals, Future Cash Flows, Artificial Neural Network, and Particle swarm optimization Algorithm

JEL: M40, M41

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1. Introduction

Cash flow is a vital source for any economic unit. The balance between available cash flows and cash needs indicates firms' economic health and guarantees the continuity of their activities. Cash flows have a central role in many financial decisions, such as stock valuation models and capital project evaluation methods. From an inter-organizational point of view, the ability to properly predict future activities' outcomes, especially future cash flows, enables the efficient management of affairs and leads to making optimum decisions in operational fields, investment, and funds. Cash flow prediction is also essential for extra-organizational users, especially the investors and creditors. Operational cash flow is further used in the new financial analyses. Thus the investment policies and resource allocation will be optimized once the operational cash flow is appropriately predicted (Khakrah Kahnamouei & Khakrah Kahnamouei, 2019)

Previous studies have examined various models to predict future cash flows of business units, and most of these studies have used regression models to predict future cash flows. The differences between studies were related to the models and presented variables, their linear and nonlinear methods, and the analysis methods. Therefore, to obtain a more accurate and comprehensive prediction, it is necessary to examine data mining methods and regression approaches. Neural networks are more important than classical methods because of their nonlinear and uncertain properties. Besides, it is worth noting that neural networks also include linear models within themselves; that is, they are more comprehensive following classical methods. It can be stated that the artificial neural network model is a powerful and efficient model that can be considered with a positive perspective in forecasts; In particular, this network is able to extract even the turbulent data, which is the most prominent feature of this model compared to other models (Khoshal Dastjerdi & Hosseini, 2010)

It is not possible to make wise judgments and decisions to choose the best solution without estimating future cash flow. Therefore, on the one hand, the problem of cash flow prediction has not been solved and needs further study according to previous research. On the other hand, due to the nonlinear relationships between accounting information, it is necessary to investigate the nonlinear and complex factors affecting future cash flow prediction to find new methods and approaches with the least deviation and error.

Because currently, a comparative study has not used regression approaches and artificial intelligence patterns in cash flow prediction and, some variables are new (a number of components of accruals and the implementation of operating flows). Their effects needed further investigation. Thus, most of the research performed in linear regression models were based on profits and accruals, while fewer nonlinear models have been used. As a result, this study uses both regression approaches and an optimized neural network model with a particle swarm optimization Algorithm to predict future cash flows on the one hand and employs new variables derived from research models Panga (2015); Farshadfar and Monem (2017); Larson et al. (2018), on the other hand. By combining these variables into a new hybrid model, we compare the results of both approaches to develop a robust, efficient model with greater explanatory power finally. This has not been investigated in other studies, and the results of this study can be more helpful in financial decisions. In this regard, we can point to its innovative aspect.

2 .Theoretical Bases & Background

2.1. Theoretical Bases

In economic theories, the value of a company is based on the current future cash flows, and the prediction of future cash has great importance. Therefore, one of the purposes of "financial reporting" is to help investors and creditors to predict future cash flows. Also, the Committee of Iran's editing accounting standards under the theoretical conceptions of the financial reporting noted that "making an economic decision by the users of the financial statements requires evaluating the business units to make cash and cash making certain". Evaluating the cash making power is facilitated by focusing on financial statements, financial functionality, and cash flows of business units and using them in forecasting expected cash flows and measuring the financial flexibility" (Mahdavi & Saberi, 2010). Making a prediction is an inevitable and crucial part of economic and financial analysis, as well as in business practice. Predictions usually lead to decision making. For instance, sales prediction will affect a firm's inventory management; financial analysts' forecasts are used to construct portfolios, monetary and fiscal policies of a country are also made concerning the country's future economic state, etc.

Various methods and techniques have been developed to enhance the predictive power of models used to forecast economic variables. In both economics and finance, academic research is important in explaining the associations and interactions between particular variables. Seeking high accuracy in prediction is of less concern (Panga & at al, 2015).

Considering the importance of cash flows, there is a need to predict cash flows in different economic decision making. National and international standardization bodies support the significance of the forecast. In this regard, researchers have repeatedly used accrual and cash accounting data for the prediction, but the results were inconsistent. There are two issues to consider when determining a company's cash flows. First, variables that are useful and contains relevant information for predicting cash flow to be identified and included in the forecasting model. Second, the type and structure of the models to be applied should be carefully selected to predict accurately. Focusing on estimates is needed to predict cash flows, and since many estimates are not disclosed in the financial statements, it can rely on accruals because most of the accruals are based on estimates. For this purpose, the relationship between the quality and components of accruals with cash flow forecasts (in terms of their usefulness in predicting future cash flows) should be examined. Investigating the relationship between accruals and future cash flows is also an important issue for corporate valuation (Choi & at al, 2015).

Olson et al. (2005) suggested that more clarification regarding the relationship between accruals and predicting future cash flows should focus on attention, and they should be disclosed if needed (Farshadfar & Monem, 2017). Recent studies have emphasized the nonlinear nature of financial information. Thus, a large number of predictive methods and the unknown factors affecting the return of wealth have caused uncertainty among investors and creditors. Consequently, they are trying to find predictive methods that make their estimates closer to reality and most accurate (Panga, 2015).

Many studies have shown the efficiency and performance of artificial intelligence models (including neural networks) compared to traditional and linear models. Because neural networks, as opposed to linear models, reflect nonlinear effects and complex interactions among variables (Hamidian & at al, 2018), neural networks' main advantage is their flexible nonlinear modeling. In artificial neural networks, there is no need to recognize the model's specific shape, and the model is based solely on the information in the data. This data-based approach is very suitable for many empirical datasets, especially when no theoretical information is available to propose an appropriate data generation process. In recent years, multilayer perceptron neural networks have been extensively studied and applied in forecasting financial markets. Despite all the benefits of multilayer perceptron networks, these networks also have disadvantages, such as the limitation of the number of input variables to the network. Using combinatorial models or combining different models (combining neural networks with bird flight algorithms) is a common way to improve predictive accuracy and overcome models' limitations. The basic idea in modeling is based on the principle that none of the existing methods is a comprehensive approach to forecast and does not apply to any situation and data type. Therefore, combining different models can improve one model's weaknesses using the strengths of the other model. Experimental and theoretical findings also show that combining different models is an effective and efficient way to improve predictions' accuracy (Kenneth & Lorek, 2019).

2.2. Empirical Background of The Study

Kenneth S. Lorek(2019) reviewed extant work on quarterly cash-flow prediction models. Due to long-term cash-flow forecasts' unavailability, he has placed greater importance upon developing statistically-based cash-flow prediction models given their use in firm valuation. Sarraf (2019), in a study titled "Cash flow forecasting by using simple and sophisticated models in Iranian companies," showed that the accrual regression model could predict future cash flows better than other tested models, and among corporate characteristics, the highest correlation belongs to sales volatility and firm size with accrual regression models. On the other hand, fitting different neural network models indicates that two structures with 8 and 11 hidden nodes are the best models to predict cash flows. Khakrah Kahnamouei and Khakrah Kahnamouei(2017), in a study titled "Providing a Model to Predict Future Cash Flow Using Neural Networks on the Pharmaceutical and Chemical Industries of Tehran Stock Market," have shown that the Multi-Layer Perceptron network is significantly more accurate than the Radius Based Function network and the three hypotheses were accepted.

The results of Farshadfar and Monem's(2017) study titled "Further evidence of the relationship between accruals and future cash flows" using Australian data shows that both working capital and non-current operating accruals are important in explaining future CFO, but financing accruals is not significant. Moreover, the accruals' asset component plays a more critical role in explaining future CFO compared with the liability component. Al-attar et al. (2017), studying "The Effect Of Earnings Quality On The Predictability Of Accruals and Cash Flow Models in Forecasting Future Cash Flows," show that earning quality cash affects the forecasting power of both cash flows and profit. In addition, when "earnings" have high-quality act better than cash flows in predicting annual future cash flow. Yarifard et al. (2016), in a study titled "the prediction of cash flows in the companies listed on the Tehran Stock Exchange," have shown that the price of the sold goods and the public and official price have a meaningful effect in forecasting the cash flows but a sale, changes in payment accounts, changes in receivable accounts, changes in inventories, tax, previous year cash flows do not have a meaningful effect in forecasting the cash flow.

Heydarpour et al. (2016) studied the rational power of the profit variables and operational cash flow in forecasting the future cash flow during three temporal periods (short-term, middle-term & long-term), and regression results show that the earnings and cash flows operations have a forecasting power for the future CFO, but their predictive powers are different. Sagafi et al. (2015), in a study titled "application of artificial neural network to forecast the future cash flow," have shown that two structures with 8 and 11 hidden neurons are the best model to forecast the cash flow. Pang (2015), in a study titled "Designing a dynamic and nonlinear model in cash flow prediction," relied on modeling and designing a new model that can fill the gap between the simple and complicated models such as the cash flow prediction model. Li et al. (2015) studied "Cash flow forecasting for South African firms," and their results demonstrated that depreciation and inventory do not have a meaningful effect on forecasting cash flows. Shobita(2013) investigated the power of accrual forecast and profit concerning future cash flows in Jordan. Their findings show that accruals and the profit can predict future cash flows, and profit is more predictive than accruals. Sagafi and Sarraf(2013), in a study titled “a model to forecast the cash flow in Iranian companies,” have shown that a random walk model can forecast operational cast flow better than the reverse accrual model. However, according to the companies' results in which the government influences their management showed that the accrual model is more suitable to the future cash flow. Rozbaksh et al. (2013), in a study titled “forecasting cash flows operations using artificial neural networks in Tehran Stock Exchange,” have shown that artificial neural networks have high capability in predicting the future cash flow because the two hidden layers with 15 and 30 neurons in each layer can predict the cash flows with 99.2 % accuracy. Arndo et al. (2012), in a study titled” The role of accounting accruals for the prediction of future cash flows” in a seven years’ temporal period in Spain, concluded that accounting accruals have a predicting power of future cash flows so that by adding accounting accruals to the current cash flows model the error-index is reduced.

2.3. Research Hypothesis

Cash flow is one of the critical resources in the economic units, and the balance between available cash and cash needs is the most critical factor in economic health. Since the judgments of many stakeholders such as investors and shareholders on the position of the economic unit are based on liquidity situation, predicting future cash flow is crucial. Continuity, survival, and existence of an economic unit largely depend on cash flows. Cash flow forecasting is important in many economic decisions because it plays a prominent role in decision-making groups such as securities analysts, creditors, and managers. These groups are interested in the company's future cash flow assessment and reach an explicit future cash flow criterion. In other words, the overall goal of fundamental analysis is forecasting the company's future cash flows.

Cash flows are the base of dividend payments, interest, and debt repayments (Sarraf, 2019). Predicting cash flows and their changes as an economic event have long been the focus of researchers', investors', managers', financial analysts', and creditors' attention. This is due to the use of cash flows in stock valuation models, payables assessment (dividends, interest, and other liabilities), risk assessment, performance evaluation of a business unit and management experience, evaluation of managers' choice of accounting methods, and use of cash flows useful for making useful decisions relevant to decision-making models. If cash flows can be properly predicted, a significant portion of the cash flow information needs will be met.

This study aims to answer whether the optimized model for predicting the Iranian capital market's future cash flows can be provided based on varying approaches. Future cash flow estimation is essential in any economic unit, reflecting management decisions in short- and long-term plans, investment, and finance projects. Without predicting cash flow, judgment, and deliberate decision making and choosing the most appropriate solution would not be possible. Therefore, we should look for a suitable model for the estimation of future cash flows. Considering the growth of the research process for forecasting cash flows in Iran, innovations in designing and modeling for prediction cash flow seem necessary. Studies are basically about models based on linear regression models; however, in this study, in addition to linear regression models (regression model), nonlinear models (Artificial Neural Network; Particle swarm optimization Algorithm) is also used and looking for an answer the question whether nonlinear model(Particle swarm optimization Algorithm) are more appropriate than linear regression model to predict cash flows or not. According to the theoretical bases and previous research, the following research hypotheses are presented to answer the above question:

Hypothesis1: The regression model is a suitable model to forecast future cash flow.

Hypothesis 2: Particle swarm optimization Algorithm is a suitable model to forecast future cash flow.

3. Methodology of the Research

3.1. Data

In this study, all listed companies on the Tehran Stock Exchange include the statistical population. To choose samples from companies from the statistical population, the following requirements were selected.

1. The sample companies should be listed on the Tehran Stock Exchange from the beginning of 2009.
2. The companies' financial statements or other required data should be available from 2009 to 2017.
3. For comparison purposes, those companies whose financial year did not end in March were excluded.
4. The investment companies and other financial intermediaries were excluded due to their different functional characteristics.

Finally, according to the requirements mentioned above, among all listed companies on the Tehran Stock Exchange, 137 companies (959 Year – Company) were selected for this study. In the present study, the combined model (particle swarm optimization Algorithm) was used to improve the accuracy of predictions and overcome the limitations of multilayer perceptron neural network models (limiting the number of input variables).

3.2. Research Methodology

This study aimed to provide a model for predicting future cash flows for listed companies in Tehran Stock Exchange using the regression model and Particle swarm optimization Algorithm. Other secondary objectives are also considered, including helping investors and creditors make optimal decisions, helping managers to disclose operating cash flow, which is considered the way to access the first target. This research is an applied and a quasi-experimental study. To analyze the relationship between the data, mainly the Rahavard Novin software and databases were used. The regression approach using the Eviews9 software and neural network model using MATLAB13 software was employed. The regression model and an artificial neural network (Particle swarm optimization Algorithm) used in this research have been explained below.

3.3. Variables, Research Model, and Neural Network Architecture

In this research, based on the theoretical and research background of Pang (2015), Farshid Far and Monem(2017), Larson et al. (2018), variables and accrual model have been used to propose an optimal model for cash flow in both approaches, the dependent and the output variables are future operating cash flows, respectively, and the other variables are the independent and input variables which are presented in Table 1. The final model of the research and its components are as follows in equations 1 and 2 bellows.

$$\begin{aligned}\boldsymbol{CF_{it+j}} = \boldsymbol{\gamma_0} + \boldsymbol{\gamma_1 CF - Cerr_t} + \boldsymbol{\gamma_2 CF - Cpaid_t} + \boldsymbol{\gamma_3 CF - NCerr_t} + \boldsymbol{\gamma_4 CF} \\ - \boldsymbol{NCpaid_t} + \boldsymbol{\gamma_5\, \Delta COA_{it}} + \boldsymbol{\gamma_6 \Delta COL_{it}} + \boldsymbol{\gamma_7 \Delta NCOA_{it}} \\ + \boldsymbol{\gamma_8 \Delta NCOL_{it}} + \boldsymbol{\gamma_9 \Delta FINA_{it}} + \boldsymbol{\gamma_{10} \Delta FINL_{it}} + \boldsymbol{\gamma_{11} \Delta INV_{it}} \\ + \boldsymbol{\gamma_{12} \Delta Ap_{it}} + \boldsymbol{\gamma_{13} \Delta AR_{it}} + \boldsymbol{\gamma_{14} DEP_{it}} \,\&\, \boldsymbol{AMORT_{it}} \\ + \boldsymbol{\gamma_{15} OTHER_{it}} + \boldsymbol{\varepsilon_{it}}\end{aligned} \quad (١)$$

$$TACi,t = \Delta WCi,t + \Delta NCOi,t + \Delta FINi,t \qquad (٢)$$
$$CFO\ it = CF - Cerr_{it} + CF - Cpaid_{it} + CF - NCerr_{it} + CF - NCpaid_{it}$$

Table 1: Research Variables, Operational Definitions, and their Measuring Methods

Variable	Symbol	How to Measure
Dependent and output variable		
future cash flows	CF_{it+j}	(the firm's net cash flow from operations of the next year)
Independent and input variables		
total accruals	TACit	Sum accruals (current operating + non-current operating + financing)
changes in working capital accruals	ΔWCit	Changes in working capital accruals during the year
changes in non-current operating accruals	ΔNCOit	Changes in non- current operational accruals during the year
changes in financing accruals	ΔFINit	changes in financing accruals during the year
cash flows from operations	CFO_{it}	the firm's net cash flow from operations, as disclosed in the statement of cash flows
changes in current operating assets accruals	ΔCOA_{it}	Changes in (total current assets – cash - current investments) during the year
changes in current operating liabilities accruals	ΔCOL_{it}	Changes in (total current liabilities - short-term facilities) during the year
changes in non-current operating assets accruals (investment)	$\Delta NCOA_{it}$	Changes in (total non-current assets - long-term investments) during the year
changes in non-current operating liabilities accruals (investment)	$\Delta NCOL_{it}$	changes(total non-current liabilities - long-term facilities) during the year
Changes in financing assets accruals	$\Delta FINA_{it}$	Changes in investments (short-term + long-term) during the year
Changes in financing liabilities accruals	$\Delta FINL_{it}$	Changes in receivable facilities (short-term + long-term) during the year
cash flows received from sales of goods and providing services	$CF\ Cerr_{it}$	cash flows received from customers (Net sales -increase/+ decrease of Net received accounts+ increase/-decrease Perceived sales –the cost of claims)
cash flows Payments For the purchases of goods and services	$CF\ Cpaid_{it}$	cash flows Payments For purchases (Net purchases +increase/-decrease of inventories -increase/+ decrease Net payment accounts increase/-decrease of Prepayment of goods
other received cash flows (except for sales of goods and providing services)	$CF\ NCerr_{it}$	(related Revenue - increase/+decrease of related receivables Revenue +increase /-decrease related Per-received revenues)
Other Payments cash flows (except for purchase of goods and services)	$CF\ NCpaid_{it}$	cash flows Payments For costs (Total costs items with the exception of non- cash costs, interest, and tax - increase /+decrease of payable costs)
Changes in inventories	ΔINV_{it}	Changes in inventory
Changes of payable accounts	ΔAP_{it}	Changes in account payable
Changes of receivable accounts	ΔAR_{it}	Changes in account receivable
tangible and intangible assets depreciation cost	DEP_{it} & $AMORT_{it}$	Depreciation and amortization
Other accruals	$OTHER_{it}$	Other accruals, calculated as earnings before interest, tax, depreciation, and amortization. (EBITDA) – (CF + ΔAR + ΔINV – ΔAP – DA).

Source: Pang(2015), Farshadfar and Monem(2017), Larson et al. (2018), and standard No 2 of IRAN accounting.

Artificial Neural Network Theory

Artificial neural networks offer a completely different approach to problem-solving, and they are sometimes called the sixth generation of computing. They provide a tool that programs itself and learns on its own. Neural networks are structured to provide the capability to solve problems without the benefits of an expert and the need for programming. They are capable of seeking patterns in data. Artificial neural networks (ANN), as they are often called, refer to a class of models inspired by biological nervous systems. Neural networks forecasting has recently enjoyed considerable success in pattern recognition and prediction and, as such, has gained considerable research attention resulting in a plethora of articles on this subject. The concept is based on computing systems that are able to learn through experience by recognizing patterns existing within a data set. Neural systems require their implementer to meet a number of conditions. These conditions include:

- A data set which includes the information can characterize the problem.
- An adequately sized data set to both train and test the network.
- An understanding of the basic nature of the problem to be solved so that basic first-cut decisions on the network can be made.
- These decisions include the activation and transfer functions, and the learning methods.
- An understanding of the development tools.
- Adequate processing power (some applications demand real-time processing that exceeds what is available in the standard, sequential processing hardware. The development of hardware is the key to the future of neural networks).

Once the necessary inputs (factors) are identified, it is relatively simple to train a neural network to form a nonlinear model of the underlying system and then use this model to generalize to new cases that are not part of the training data. (Kumar &Walia, 2006)

The model consists of an output variable, which is future operating cash flow. At the next stage, the data were prepared. The preparation of data is one of the complicated stages in the use of neural networks. A part of this complexity depends on the selection of proper training patterns. Another part depends on changes in the scale of data because the best status for neural networks is when all the inputs and outputs range from 0 to 1.Since it is not possible to predict which of the functions will produce the best response at the beginning of the study, a neural network with hypothetical functions should be considered, and the best results can be obtained after analyzing and evaluating the results. Hypothetically, based on the researchers' experience, the Levenberg-Marquardt training function, the fastest Gradient Descent With Momentum, and the Mean Square Error function are used as the default functions. In backpropagation networks, the Hyperbolic Tangent Sigmoid, log sigmoid and linear function are used. In the beginning, the transit function is used for the hidden layers, and the pure function is used for the output layer. In the neural network, layer-by-layer calculations are performed, and the output is calculated. First, the outputs of one layer of nerve cells are calculated, and these outputs are used as inputs for the next layer. Then, from these inputs, the second layer's outputs are calculated, so the process is continued to obtain the output vector of the network. In the meantime, the learning functions are of particular importance. The particle swarm optimization algorithm (PSO) structure is presented in fig 1.

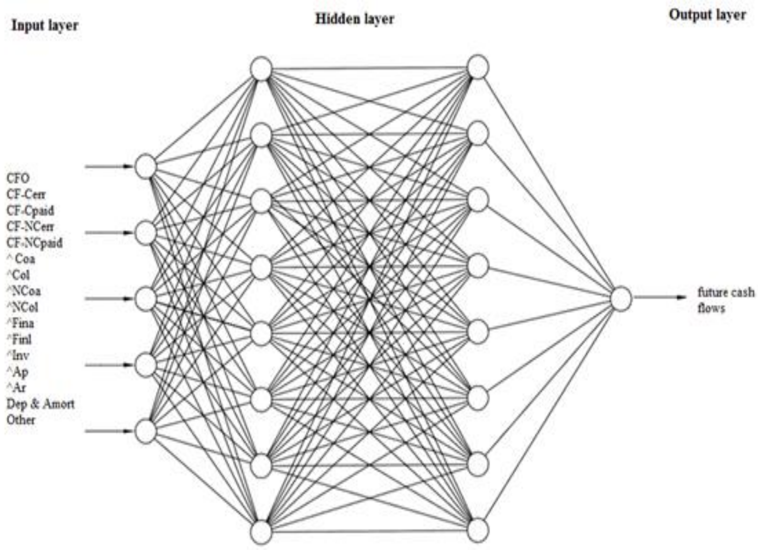

Fig 1: Particle Swarm Optimization Algorithm (PSO)

3.4. Implementation of Particle Swarm Optimization Algorithm

To propose a neural network model for forecasting future cash flows, the necessity of standard normalization for the model's appropriacy will be discussed. Then, the number of network hidden layers, the number of neurons in each layer, learning algorithm, transfer function, application function, and the number of repetitions, the size of learning and training collection will be specified for which there is no unique systematic method. Therefore, the best-designed network will be achieved by trial and error.

In recent years, due to the limitations of mathematical methods, lots of research has been done on the use of evolutionary algorithms for optimization. One of the most effective methods is the bird flight algorithm. In this study, according to the study of Asadi and Naqdi (2018), combining and developing the integrated neural network model with particle swarm algorithm (Birds' Flight) for prediction were implemented as follows.

Table 2: The Summary of Particle Swarm Optimization Algorithm (PSO) Process

Parameter	Description
Network type	Particle swarm optimization Algorithm(PSO) Multi-Layer Artificial Neural Networks (MANN) (Feedforward) by a new function
Normalization of data	mapminmax function
Removing random data	Dividend function
The number of Neurons of hidden, input, and output layers	15 neuron, 4-12 neuron, 1 neuron
Size of population	20
Weight and inertia coefficient	{1- 0} and 0.5
Number of particles	85
Cognitive and collective learning coefficient	1.5 - 2
The number of repetitions(Epochs)	500
numbers of collection	Training 65%, accreditation 10%, and test 25%
evaluation criteria and choosing the best structure to experimental results and test	Mean squared error (MSE) Root-mean-square error(RMSE) Normalized Mean Squared Standard Error (NMSE) Mean Absolute Error(MAE) Mean Absolute Percentage Error(MAPE) the correlation coefficient(R2)
Choosing the most efficient variables to forecast	Sensitivity Analyze (weight factor)

1.Building the initial population and evaluating it
2. Determining the best personal memories and the best collective memories
3. Updating speed and position and evaluating new responses
4. if stopping conditions were not met, we would return to step 2
5. End.

The summary information of the main parameters and fitting stages of the neural network optimized with the research flight pattern is shown in Table 2.

4. Research Findings

4.1. Descriptive Statistics

Table 3: Descriptive Statistics of Research Variables

Variable/Statistic Index	Mean	Median	Minimum	Maximum	Standard Deviation
CF	0,169	0,138	-1,007	1,356	0,206
CFO	0,143	0,123	-0,723	1,147	0,165
COA	0,451	0,562	-0,011	2,213	0,151
COL	0,154	0,069	-0,854	1,054	0,214
NCOA	0,129	0,513	-0,754	3,333	0,201
NCOL	0,201	0,134	-0,087	2,041	0,176
FINA	0,098	0,017	-0,314	0,821	0,037
FINL	0,112	0,035	-0,425	1,678	0,142
CF_Cerr	1,070	0,867	-0,0۲۳	11,017	0,858
CF_Cpaid	0,992	0,776	0,002	10,336	0,860
CF_NCerr	0,117	0,057	0,000	1,812	0,170
CF _NCpaid	0,048	0,034	0,001	0,622	0,048
INV	0,065	0,062	-1,512	1,563	0,141
Ap	0,041	0,026	-0,289	0,851	0,094
AR	0,065	0,031	-0,721	2,021	0,174
DEP & ***AMORT***	0,021	0,017	0,013	0,126	0,017
OTHER	-0,048	-0,037	-3,321	1,863	0,302

Number of Observations: 959
source: Calculations of the Research

Descriptive statistics (regression and central tendency indices) of the research variables are provided in Table 3. The main central tendency index is the “mean” which shows the balance point and distribution mean center. The mean index of all variables was positive, and the highest index was related to cash flows received from sales of goods and providing services (CF-Cerr) with 1.070 around which most of the data had been concentrated. Generally, the regression parameters are criterion to determine the regression value from each other or their regression value concerning the mean. One of the most important regression parameters is the standard deviation. The amount of this parameter for paid cash flows variable to purchase goods and services (CF-CAPID) is 0.86, and for the variable of tangible and intangible assets depreciation, it is 0.017 that shows these two variables have the lowest and the highest regression value among the research variables.

4.2. Results of the Regression Approach

Table 4: Results of the Normality and Stability of Dependent Variable (Research) and Flimer and Hasman Model Test.

Variable	**Jarque-Bera Test**		**Lewin, lin, Chu Test**		**Result**
	Statistic	Prob.	Statistic	Prob.	
CF	1369,6	0,000	-20	0,000	Normal-Stable
Model/Test	Redundant Fixed Effects Tests		Hasman Test		Model Process Method
	Statistic	Prob.	Statistic	Prob.	
The First	1,816	0,000	222,18	0,000	Fixed Effects, Panel Data

source: Calculations of Research

Because the statistical probability of the Jarque-Bera test in Table 4 for the dependent variable of the future operating cash flows is smaller than the 5% error level, the null hypothesis of the normality of the variable mentioned above is rejected. It means that the data does not follow the normal distribution for the dependent variable. If the model is big enough in size (many of the resources consider thirty observations and so as a big size), even if the distribution of the estimated proposed model statements is normal, the calculated co-efficient will have minimum variance, and they will be efficient, and we can rely on these models to test the research hypothesis (Badavarenahndi & at al, 2019). As a result, and considering the big size of this research sample, it is assumed that the research's dependent variable is normally distributed. Table 4 shows that the significance level of the Lowin, Lin, and Cho test is less than 5% for the dependent variable of the research, which shows the research's reliability. Therefore, the confidence level of 95% shows that the dependent variable for the data was reliable and did not have a unique root. In addition, based on the results in Table 4 Flimor significance level in the research model is less than 5%. Therefore, the Hasman test will determine the regression type. According to the Hasman test results, when the Flimor significance level is less than 5%, the fixed effect panel data method is used, and if it is more than 5%, the random data–panel method is used. The results of the tests indicate the fixed effects panel data method.

Table 5: Results of the Regression Test

Variable	Coefficient	Std. Error	t-Statistic	P-Value
C				
CF_Cerr	0.133	0.051	2.6	0.009
CF_Cpaid	-0.118	0.047	-2.47	0.013
CF_NCerr	0.271	0.063	4.285	0.000
CF_NCpaid	-0.019	0.217	-0.087	0.030
ΔCOA	0.257	0.041	6.237	0.000
ΔCOL	-0.127	0.034	-3.651	0.000
$\Delta NCOA$	0.0348	0,025	1,378	0,008
$\Delta NCOL$	0.026	0.025	1.052	0.292
$\Delta FINA$	0.148	0.062	2.373	0.017
$\Delta FINL$	0.007	0.05	0.157	0.074
ΔINV	0,257	0.054	5,154	0.000
ΔAp	-0,21	0,061	-3,25	0.002
ΔAR				
DEP & $AMORT$				
$OTHER$				
R-squared	0.789	F-statistic	16.8	
Durbin-Watson stat	2,15	Prob(F-statistic)	0.0000	
Adjusted R-squared	0.655			
source: Calculations of Research				

As the results of the Table 5 show, the calculated significant level for each of the thirteen independent variable cash flows received from sales of goods and providing services(CF-cerr), other received cash flows (except for sales of goods and providing services) (CF-NCerr), cash flows payments for the purchases of goods and services(CF-Cpaid), other payments cash flows (except for purchase of goods and services) (CF-NCpaid), current operating asset accruals (COA), current operating liability accruals(COL), non-current operating asset accruals (NCOA), financing asset accruals (FINA), changes in account receivable (AR), changes in account payable(AP), changes in inventories(INV), tangible and intangible assets depreciation cost (DEP & AMORT) and other accruals (other) is smaller than 5% error level, and the calculated coefficient for ten variables is positive, and for three variables it is negative. Therefore, it can be said that cash flows received from sales of goods and providing services(CF-cerr), other received cash flows (except for sales of goods and providing services) (CF-NCerr), cash flows payments for the purchase of goods and services(CF-Cpaid), other payment cash flows (except for purchase of goods and services) (CF-NCpaid) current operating asset accruals (COA), current operating liability accruals(COL), non-current operating asset accruals (NCOA), financing asset accruals (FINA), changes in accounts receivable (AR), changes in accounts payable(AP), changes in inventories(INV), tangible and intangible asset depreciation cost (DEP & AMORT) and other accruals (other) have a direct and meaningful effect on future cash flows of the accepted companies in Tehran Stock Exchange. Furthermore, cash flow payments for the purchase of goods and services (CF-Cpaid), current operating liability accruals (COL), changes in accounts payable (AP) have a meaningful reverse effect on future cash flows of the accepted companies in Tehran Stock Exchange". Nevertheless, the significant calculated level for the variables of non-current operating liability accruals (NCOL) and financing liability accruals (FINL) is larger than 5%, implying that these variables' effect on forecasting cash flows is not meaningful. In addition, according to the results from the balanced determination coefficient, which is 65.5 %, it can be said that 65.5% of the dependent variable changes can be explained. Since the Durbin –Watson statistic of the model is nearer to 2(2.15), it can be said that there is no first-order autocorrelation in this model (confirming one of the regression hypotheses). In addition, the results of Table 5 show that the F test significant level is less than 5%. Since the F statistic shows the model's total reliability, it can be stated that this model is %95 meaningful and has high reliability. Based on the research model results, the regression model is a suitable one for forecasting future cash flows. Thus, the first research hypothesis is accepted, and this model with 13 effective and predictive variables is able to forecast future cash flows as follows:

$$\begin{aligned} \boldsymbol{CF_{it+j}} = \boldsymbol{\gamma_0} &+ \boldsymbol{\gamma_1 CF - Cerr_t} + \boldsymbol{\gamma_2 CF - Cpaid_t} + \boldsymbol{\gamma_3 CF - NCerr_t} \\ &+ \boldsymbol{\gamma_4 CF - NCpaid_t} + \boldsymbol{\gamma_5\, \Delta COA_{it}} + \boldsymbol{\gamma_6 \Delta COL_{it}} \\ &+ \boldsymbol{\gamma_7 \Delta NCOA_{it}} + \boldsymbol{\gamma_8 \Delta FINA_{it}} + \boldsymbol{\gamma_9 \Delta INV_{it}} + \boldsymbol{\gamma_{10} \Delta Ap_{it}} \\ &+ \boldsymbol{\gamma_{11} \Delta AR_{it}} + \boldsymbol{\gamma_{12} DEP_{it}} \,\&\, \boldsymbol{AMORT_{it}} + \boldsymbol{\gamma_{13} OTHER_{it}} + \boldsymbol{\varepsilon_{it}} \end{aligned} \quad (3)$$

4.3. Results of Particle Swarm Optimization Algorithm (PSO)

A convergence diagram of the particle swarm optimization algorithm based on the number of iterations is presented in diagram1. The horizontal axis indicates the number of evaluations of the target function during optimization. As shown, the particle optimization algorithm is rapidly converging, and from the number of 150 evaluations on, the target function value remains constant, indicating the algorithm's power to optimize.

In this current study, fitting different neural network models particle swarm optimization algorithm (PSO) in the form of 9 structures were fitted. In this study, due to the paper space's limitation, only the best neural network model structure with eight hidden neurons in Table 6 was presented. Based on the model's predictive accuracy, the least square error of standard error was (4.68), and the highest correlation coefficient was (0.95), and this structure is the best in predicting future cash flows.

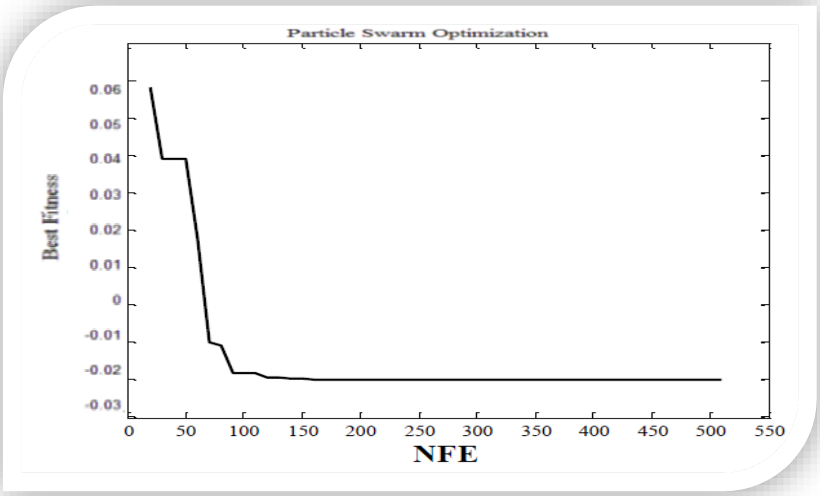

Diagram 1: Convergence Chart of Particle Swarm Optimization Algorithm

Table 6: Results of Neural Network Performance Evaluation Criteria Particle Swarm Optimization Algorithm(PSO) (8 Hidden Neuron).

Evaluation Criteria and parameters	**Amount of**	
	Training Data	**Test Data**
Mean Squared Error (MSE)	٩,٠٤	٤,٦٨
Root Mean Squared Error (RMSE)	٦,١	٤,٥
Normalized Mean Squared Standard Error (NMSE)	١,٠٥	٠,٦٣
Mean Absolute Error (MAE)	٥,١	٣,٨
Mean Absolute Percentage Error (MAPE)	٩٢	٧٣,٩
R Squared(R2)	٠,٨٨	٠,٩٥

source: Calculations of the research

Table 7: The Results of Sensitivity Analyze (Weight Factor) Inputs of the Particle Swarm Optimization Algorithm(PSO)

Variable	Sensitivity Analyze
Cash flows from the sale of goods and the provision of services	
Cash flows for the purchase of goods and services	
Other cash flows (except sales of goods and services)	
Other paid streams (except the purchase of goods and services)	
Operating Assets Accruals	
Current operating debt accruals	
Non-operating assets accruals	
Non-performing operating debt accruals	
Financing Accruals	
Financing Accruals	
Changes in the inventory of goods	
Payable Account Changes	
Payable Account Changes	
The cost of depreciation of tangible and intangible assets	
Other accruals	
Financing Accruals	

source: Calculations of the Research

The sensitivity analysis results of the research variables are presented in the best structure of (8 hidden nodes) particle swarm optimization algorithm(PSO) in Table 7. Sensitivity analysis was used to select the most influential variable in predicting cash flows. Naturally, the greater the sensitivity analysis (Weight coefficient) of the variable, the greater the impact and weight on the network output and the prediction of future cash flows. The sensitivity analysis process shows how sensitive the model is to its input variables. In this study, according to Asadi and Naqdi (2018), we have obtained the input variables' sensitivity coefficient values by dividing the total network error in the absence of one variable by the total network error in the presence of all input variables. As can be seen from the above diagram results, almost all the weighting coefficients of the variables are larger than one and close to one, indicating the ability of almost all variables to predict cash flows. And among the variables, operating current assets accruals (COAs) with a weighting coefficient of (0.247) and NCOLs with a coefficient (0.101) have the highest and the least influence on the prediction of future cash flows, respectively. As a result, the second hypothesis is accepted, and this model predicts future cash flows with all 15 variables. This model predicts the future cash flows with 15 predictive variables by the following relationship (4):

$$\begin{aligned} CF_{it+j} = \gamma_0 &+ \gamma_1 CF - Cerr_t \gamma_2 CF - Cpaid_t + \gamma_3 CF - NCerr_t + \gamma_4 CF - NCpaid_t + \gamma_5 \Delta COA_{it} \\ &+ \gamma_6 \Delta COL_{it} + \gamma_7 \Delta NCOA_{it} + \gamma_8 \Delta NCOL_{it} + \gamma_9 \Delta FINA_{it} + \gamma_{10} \Delta FINL_{it} \\ &+ \gamma_{11} \Delta INV_{it} + \gamma_{12} \Delta Ap_{it} + \gamma_{13} \Delta AR_{it} + \gamma_{14} DEP_{it} \,\&\, AMORT_{it} + \gamma_{15} OTHER_{it} \\ &+ \varepsilon_{it} \end{aligned} \qquad (۴)$$

The actual and predicted values of operating cash flows based on a neural network model optimized with the bird flight model is illustrated in Diagram 2. As the Figure shows, the results of a neural network optimized with the bird flight model are closer to the actual results.

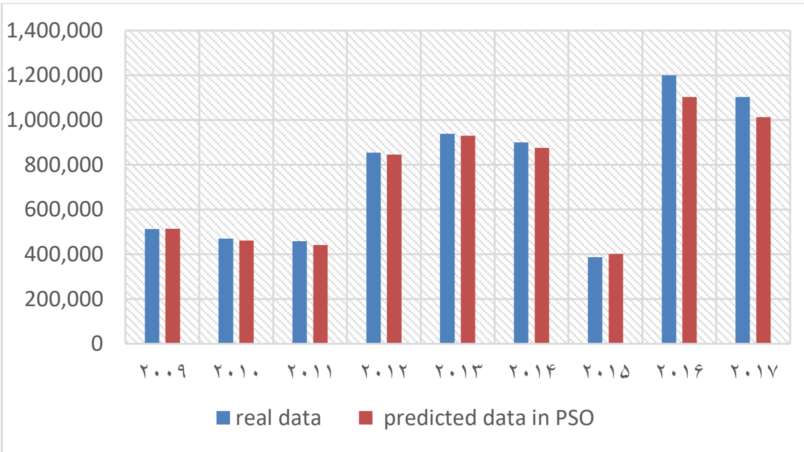

Diagram 2: Comparison of Real Data with Predicted Data in PSO

6. Conclusions and Suggestions

The future forecasting has been a necessity in everyday life and is a common area of interest in many scientific fields. One of the areas in which prediction has great importance is economical and financial issues. The effect of the stock exchange market in the economic development of a country is undeniable. The main task of this market is the effective operation of the capitals and the optimal allocation of the resources (Etemadi & at al, 2018)

Previous studies have examined various models to forecast future cash flows of the business units, and most of these studies have used regression models to forecast future cash flows. Therefore, it is necessary to try other new methods to attain a more exact prediction. In a world where there are tremendous changes in the economy every moment, predicting future events will be a key factor in capturing profit opportunities. While traditional techniques such as regression have proved to be ineffective in some cases, many people are interested in predicting future events more accurately.

Regarding the alignment of the results of this study with those of other studies, it can be stated that there is no similar study with these variables, so it cannot be thoroughly compared with other research results. The results of the first hypothesis of the study showed that "the regression model with 13 predictor variables is a proper model for predicting future cash flows". The results of this hypothesis are in line with the results of the Farshadfar and Monnem's (2017); Shubita (2013); Arendo et al.' s(2012); Saghafi & Sarraf's (2013); Sarraf's (2019) studies and the results of the second research hypothesis show that "particle swarm optimization algorithm (PSO)" with 15 predictor variables is a proper model for predicting future cash flows. Due to the lack of a similar study using this method (with similar variables), it was impossible to accurately compare the results.

Therefore, based on this study's results, the components of the operating cash flows compared with accruals components have a greater relative ability to predict future cash flows. However, it is recommended that investors, financial analysts, and other financial statement users pay more attention to new data mining techniques in their predictions so that they can make more rational decisions. Based on the results of this paper, creditors evaluate customers' ability to generate cash flows, investors to cash flow prediction in business units, and managers in various decision-making that require cash flow estimations and analysts in interpreting and helping users could benefit from this research results.

Considering the future research, it is suggested that a study under the same title with other new models of artificial intelligence (neural network optimized with a genetic algorithm, support vector machine, etc.) can be performed, and its results can be compared with those of this study. Given the new variables introduced in this study with which to date no studies have been conducted using a similar model in Iran, it is suggested that research under the same title together with future profit prediction and earning quality can be performed using modern patterns and the results can be compared. Besides the variables studied in this study, other variables can help improve the proposed models so that new variables can be incorporated with the existing variables with the mentioned patterns. Since predicting cash flow is a multifaceted approach, it is convenient that other approaches can be investigated, too. Finally, it is recommended that future studies of probable networks whose structure includes one input and three information-processing layers (pattern layer, classification, and output layer) can be investigated and compared to the results of this paper.

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