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Cash flow forecasting by using simple and sophisticated models in Iranian companies

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Abstract

Cash flow is one of the critical resources in the economic unit and the balance between available cash and cash needs is the most important factor in economic health. Since judgments of many stakeholders such as investors and shareholders about the position of the economic unit are based on liquidity situation, so predicting future cash flow is crucial. In this research, the impact of cash and accrual items on cash flow forecasts has been studied. Providing a proper model to predict operating cash flows and review some important characteristics of cash flow forecasting regression models, using a multilayer perceptron and determining the best model by using accrual regression model variables for predicting cash flows. For this purpose, 287 firms listed in Tehran Stock Exchange during 2008 to 2017 were studied; Linear and nonlinear regression, correlation coefficient and artificial neural network statistical methods have been used for data analysis and predictive power of powers was compared by using the sum of squared prediction error and coefficient of determination. Results showed that the accrual regression model can 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, results of fitting different neural network models indicate that two structures with 8 and 11 hidden nodes are the best models to predict cash flows.

Keywords: Predicting cash flows, Future cash flows prediction models, Accruals, Artificial Neural Network.

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Introduction

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.

The importance of predicting cash flows has been supported by [1]IASC and [2]IFRS and in this regard, researchers have consistently used cash and accrual accounting data for this prediction (Mirfakhreddini et al, 2009). Operating cash flow projections is not possible by using historical operating cash flows, but it can be achieved by using historical returns. Simultaneous use of operating cash flow and historical operating profit will improve the prediction model (Modarres et Dianati, 2003). Therefore, the obligation regression model can predict future operating cash flows better than other models (Sarraf et others, 2013).

Future cash flow estimation is so important in any economic unit which reflects management decisions in short and long term plans, investment and finance projects. Without predicting cash flow, judgment and deliberate decision making and choose the most appropriate solution won't 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. Researches are basically about models based on profit and accruals; however, in this study, in addition to linear regression models (accrual and cash flow regression models), nonlinear regression model is also used and looking for answer the question that whether accrual regression models are more appropriate than cash flow regression models to predict cash flows or not; and comparing these models and choose the most suitable model for Iranian companies, the impact of firm's operating characteristics on cash flow forecasting models such as profit and sales growth, firm size and end-of-period inventory are considered in models; Additionally, data analysis by using

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[1]the Inter-Agency Standing Committee

[2] International Financial Reporting Standards

artificial neural network and variables influence strategy is used to select the most effective variable in forecasting operating cash flows.

Literature Review and Prior Researches

Business continuity is one of the first considerations and cash is one of the most critical factors in the company's survival. Only firms can survive which are profitable and meet their cash needs (Lie, 2006). The so-called profitability is the firm's no diseases, power of liquidity and business continuity demonstration (Sarraf et al, 2013). Future cash flow forecasting is so important for various purposes including securities valuation, evaluation and selection of capital projects, capital budgeting, risk assessment, and liquidity. This prediction is a basis of valuation methods (Barth et al, 2001). Financial analysts and investors are often use accounting information as part of economic decision making in order to estimate the company's ability to generate future cash flows. Timeliness and relevance of accounting information and operating cash flows to predict future operating cash flows will help investors make better-informed decisions. This information can be provided on cash or accrual basis accounting.

Accrual accounting is an accepted accounting method for financial statements which is recommended by IASB (2001, paragraph 22) and its items can be used to forecast cash flows. Accordingly, business transactions are reported periodically irrespective of payments, the main reasons for the accrual development accounting system are scheduling problem reduction and cash flow compliance to evaluate the company's performance (Dechow, 1994; Cheng, Lieu et Schaefer, 1997). Given the fact that there are criticisms in every category, the nature of accruals is criticized for two reasons: (1) being subjective; (2) through manipulating profits, distorts performance.

Based on criticisms, it is possible that accrued earnings would have less ability to predict cash flows; therefore, accounting information users may return to cash accounting (Sharma, 2003; Teoh et al, 1998).

On the other hand, cash accounting is a financial reporting system that describes business unit performance in cash. It is a base for cash inflows and outflows periodic compliance and also free from transactions and arbitrary allocations. Inputs include cash receipting from trading operations and long-term financial activities and outflows include replacement payments, capital increase, tax, interest, dividends and........ (Lee, 1981).

Cash accounting only recognizes cash transactions (Birt, Chalmers, Beal, Brooks and Oliver, 2008). Profit in the accounting period is recorded only when incomes and expenses turn into cash in the same period. This is precisely in contrast to accrual accounting. Conservatism in cash accounting is more than accrual accounting because it records only real cash flows and contrary to accrual accounting, does not predict cash flow events in a reasonable and reliable manner (Elliott and Elliott, 2007).

Concepts addressed in cash and accrual accounting are effective in reporting information and cash inflows and outflows. As a result, some models are based on cash accounting information and some others on accrual. Variables in each model influenced by raised accounting concepts. The following table summarizes cash and accrual accounting comparison.

Table1. Comparative Summary of Accrual and Cash Accounting (Sarraf, 2013)

Accrual Accounting	**Cash Accounting**
All economic transactions carried out during the financial period are reported regardless of cash flow timing.	Only transactions are reported that turns intocash throughout the financial period.
Costs with corresponding revenues are adjusted regardless of cash flows.	Revenues are recorded at the time of receipt and costs when payment is made.
Leads to better performance measurement due to profits correct reporting.	If cash receipts and payments occur between several periods, mismatches occur and lead to deviations in performance measurement.
It is difficult to prepare and needs to have a mental understanding.	Preparation is comfortable, objective and real.
It is recommended by accounting standards as the base for preparing financial statements.	Introduced by accounting standards to provide supplemental information.
Sophisticate	Simple
It is Comprehensive and detailed because includes cash and non-cash information, provides other relevant information, such as resources (assets) and obligations (liabilities) and the ability to manage resources and obligations.	It is less comprehensive because only reports cash information.
Provides information for efficiency and effectiveness of assets.	Provides far less information than accrual-based the approach regarding productivity.
It has a Relative trustability.	It has more credibility but cannot be relied upon in decision-making.

In order to increase model predictability, the company's operational characteristics such as inventory to future sales ratio sustainability, sales volatility, profitability, and firm size can be used (Yoder, 2006). The company's specific inventory volatility ratio (IRVOL) is the change in inventory to future sales which is expected to be related to accrual models predictive power. Profits and sales volatility reflects the instability of the business operating environment. Increasing cash flow volatility leads to a higher prediction error in accrual models and cash flows. In addition, sales and earnings volatility effects on accrual model parameters volatility and sales estimation errors. Sales volatility has changed model predictive power; direction determination of sales volatility effect on predictive power can be investigated. On the other hand, large corporations are more stable in terms of accrual model parametric (accrual specific coefficients) through more diversity in sales and purchases but in smaller companies, model parameters are affected by a relatively small number of contracts or customers (Yoder, 2006).

Empirical studies indicate that to predict operating future cash flows, the model derived from operating cash flows and accruals combination is superior to profit-based or operating cash flow models (Barth et al,2001; Al-Attar et Hussain,2004; Ebaid,2011; Francis et al,2012). In addition, accrual components separation and their combination with operating cash flows seem to increase the aggregated profit predictive power. Empirical evidence suggests that the model derived from combination of operating cash flows with separated accrual components to predict future operating cash flows exceeds models that are based solely on operating cash flows or profit as well as on models derived from combination of operational cash flows and accrual component (Barth et al, 2001; Al-Attar et Hussain, 2004; Ebaid, 2011; Francis et al, 2012). Barth et al, Al-Attar etHussain, Ebaid, Francis et al concluded that breakdown of profit into operating cash flows and accruals increases profits ability to predict future operating cash flows and accruals separation from its components will improve profit predictive power.

Other studies indicate that historical operating cash flows are more predictable than historical profit (Arthur et al, 2007; Barth et al, 2001; Chotkunakitti, 2005; Farshadfar, 2008; Habib, 2010; Penhamet Yehuda, 2009 and Seng, 2006). Few studies have argued that there is no significant difference between these two types of information (Arnold et al, 1991; Lorek et Willinger, 2009; Mcbeth, 1993; Pfeiffer, 1998). Also, Francis and Eason (2012) studied the relationship between accruals and operations cash flow forecasting. For this purpose, two models were compared. The first model was a random walk cash flow model and the second one was a reversal accrual model in which current cash flow is accompanied by changes in receivables, payables, and inventory. Researchers' findings suggest that cash flow forecasting with accrual components is more accurate than simple prediction based on the random walk model.

Janjani (2015) concluded that operating cash flows using Iran [3]GAAP compared to US GAAP have no effect on projected future cash flow.

Kordestani (1995) in his research, which followed the Finger method, examined entire accounting profitability to predict future earnings and cash flows. Results showed that none of the models are able to forecast future cash flows to be close to real items; however, accounting profit is a superior predictor of cash flows.

Saghafi and Fadaie (2007) found that accrual-based models have the ability to anticipate more than models only consist of cash flows.

Mahdavi and Saberi (2010) in their study showed that breakdown of profit into cash and accrual components will increase the ability to forecast cash flows. Projected cash flows based on disaggregated earning models can predict future operating cash flows better than the other tested models.

Mahmoud Abadi and Mansouri (2011) examined the role of discretionary and non-discretionary accruals in predicting future cash flows for the period 2001-2009 and comparing two independent sample means (t-test) was used. The results of the research showed that discretionary and non-discretionary accrual variables do not have the ability to predict future cash flows (Sarraf et al, 2013).

Sarraf et al (2013) studied cash and accruals impact on operating cash flow forecasting. They use correlation coefficient and linear and nonlinear regression to analyze data. Findings suggest that the accrual regression model can predict future operating cash flow better than other tested models.

Based on Saghafi and Sarraf's findings (2014), the random walk model in comparison with a negative accrual model can predict operating cash flow better. Meanwhile, corporations in which the government has influence, accrual model is more proper for estimated future cash flows.

Saghafi et al (2015) used a multilayer perceptron neural network by determining the superior model using accrual regression model variables in

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[3] Generally Accepted Accounting Principles

order to predict future cash flows. Results showed that a multilayer perceptron neural network is an appropriate model to predict the firm's cash flows; in addition, government-owned companies have no significant effect on cash flow forecasting.

Kenneth S. Lorek (2019) reviewed extant work on quarterly cash-flow prediction models. Due to the unavailability of long-term cash-flow forecasts, he had placed greater importance upon the development of statistically based cash-flow prediction models given their use in firm valuation.

Farshadfar and Monem (2013), provided further evidence that disaggregating operating cash flow into its components enhances the predictive ability of aggregate operating cash flow in forecasting future cash flows. They also found that cash received from customers and cash paid to suppliers and employees complement each other in enhancing the overall predictive ability of cash flow components.

Yun Li, et al, (2015), applied models in the extant literature that have been used to forecast operating cash flows to predict the cash flows of South African firms listed on the Johannesburg Stock Exchange. The reported results show that the inclusion of more explanatory variables does not necessarily improve the models. They proposed the application of a moving average model in panel data and vector regressive model for multi-period-ahead prediction of cash flows.

Sebastian M.Blanc and ThomasSetzer (2015), proposed and empirically tested statistical approaches to debiasing judgmental corporate cash flow forecasts. They compared different forecast correction techniques such as Theil's method and approaches employing robust regression, both with various discount factors. The findings indicated that rectifiable mean, as well as regression biases, exist for all business divisions of the company and that statistical correction increases forecast accuracy significantly.

Linna Shi and et al, (2014), investigated how analyst cash flow forecasts affect investors' valuation of accounting accruals. They found that the strength of the accrual anomaly documented in Sloan (1996) is weaker for firms with analyst cash flow forecasts, after controlling for idiosyncratic risk, transaction costs and firm characteristics associated with the issuance of cash flow forecasts. They further showed that this reduction in the mispricing of accounting accruals is at least partially attributed to the improved ability of investors to price-earnings manipulations embedded in accruals.

RattachutTangsucheeva and VittaldasPrabhu (2014), developed stochastic financial analytics for cash flow forecasting for firms by integrating two models: (1) Markov chain model of the aggregate payment behavior across all customers of the firm using accounts receivable aging and; (2) Bayesian model of individual customer payment behavior at the individual invoice level. The proposed model is back-tested using empirical data from a small manufacturing firm and found to differ 3–6% from actual monthly cash flow, and differs approximately 2–4% compared to actual annual cash flow. They underlined that the forecast accuracy of the proposed stochastic financial analytics model is found to be considerably superior to other techniques commonly used.

According to the above-mentioned researches which summarized, the projected cash flow dilemma still remains unresolved and requires further researches. Therefore, in view of expected future cash flows importance in decision-makings and various roles of cash and accrual models in these estimations, this paper considers Iran's specific circumstances and designs a new model to predict cash flow which will increase the ability to estimate future cash flows among cash flow prediction models.

Nasser A. and Spear Mark Leis (1997), developed three supervised artificial neural networks (general regression, backpropagation, and probabilistic) to predict the accounting method choice by oil and gas producing companies. They compared the prediction accuracy generated by the artificial neural networks with those generated using logit regressions and multiple discriminant analysis. Their three-layer general regression network performed much better with the overall prediction error ranging from 8% to 11%, while this figure is ranging from 24% to 43% by using traditional models.

Research Hypothesis

With regard to theoretical foundations and the main purpose of this research, the following hypotheses are presented:

H_1: Forecasting cash flows based on accrual models are better than predictions based on cash flow models.

H_2: The ability to predict accrual models in comparison with cash flow models will decrease with changes in ending inventory to future sales ratio.

H_3: The ability to predict accrual models will change compared to cash flow models, with sales and profit volatility.

H_4: The ability to predict accrual models in comparison with cash flow models will increase with firm size.

H_5: Multi-layer neural network is an appropriate model for predicting the firm's cash flow.

H_6: State-owned Company has an effect on the arrangement of accrual regression model variables for a predictable cash flow based on an artificial neural network.

Statistical Population and Sampling

In order to collect homogeneous information from all members of the population and no reliable sources of financial information for companies outside Tehran Stock Exchange, the statistical population includes firms listed in Tehran Stock Exchange with following conditions:

- According to the period 2008- 2017, the company should be listed on Tehran Stock Exchange in 2008 and will not be removed from the list by the end of 2017.
- For consistency, all Company's fiscal year should end on 31 March.
- Investment and financial companies will be removed because there is not a clear boundary between operational and financing activities for them.
- For integration and expansion, companies should not cease activities and its financial period not changed during this period.

Based on above criteria, 484 listed companies, 287 companies selected as samples and 1663 year/company data were used which 73 years/companies data related to companies that government came in and for this purpose, sample data have been collected from Tehran stock Exchange Website and RahavardNovin and TadbirPardaz applications.

Research Methodology

In order to investigate the hypotheses of this study, multiple linear and nonlinear regression methods, Spearman correlation coefficient (hypotheses 2-4) and artificial neural network are used. It should be noted that the ability to predict models was compared by using their sum of squared prediction errors; meanwhile, the mean forecast error and coefficient of determination were also used. All operations related to data management and their analyses were done in excel spreadsheets and SPSS software version 19. In the following, variables, regression models and an artificial neural network that used in this research have been explained.

1.Variables Used in the Research

Table2. Variables used in the research

NO	Abbreviations	Definition
1	CFO	Cash flow from operating activities
2	ΔAR	Changes in accounts receivable
3	ΔInv	Changes in inventory
4	ΔAP	Changes in accounts payable
5	ΔACCEXP	Changes in accrued expenses payable
6	ΔACCIT	Change in Income tax payable
7	S	Annual net sales
8	Inv	Ending inventory
9	α	Accounts receivable to sales ratio AR_t/S_t
10	β	Ending payables to purchased goods plus operating costs $AP_t/PURCH + OE$
11	γ	Ending inventory to projected cost of goods sold $INV_t/COGS_{t+1}$
12	π	Gross Profit to Sales percentage $S_t - COGS_t/S_t$
13	λ	operating costs to sales ratio OE_t/S_t
14	COGS	the projected cost of goods sold (1-π) $E(S_{t+1})$
15	Gover	Companies in which the government has significant influence (as defined by Supreme Audit Court of Iran)
16	ΔS	Changes in sales from one period to another
17	EΔSales2	changes in expected sales form period t+1 to t+2
18	AVgTA	Average total assets ($TA_t + TA_{t-1}/2$)
19	IRVOL	Inventory Turnover specific ratio ($\Delta Inv_t/S_{t+1}$)
20	SALESVOL	Sales Volatility ratio ($S_{t+1}-S_t/AVgTA$)
21	EARNVOL	Earning Volatility ratio (ΔEARN/AVgTA)

2.Cash Flow Based Forecasting Model

In cash flow based forecasting models, current cash flows are used as a criterion for forecasting future cash flows that include cash flow random walk and cash flow regression models, which will be reviewed further.

2.1. Cash Flow Random Walk Model (Cfrw)

The cash flow random walk model operates randomly and in this model, expected future cash flow is equivalent to current operating cash flows. The cash flow random walk model has been used as a criterion in Bowen et al (1986) and Francis and Eason's (2012) researches.

$$E(CFO_{i,t+1}) = CFO_{i,t} \quad (1)$$

2.2. CASH FLOW REGRESSION MODEL (CFREG)

Cash Flow Regression model, predicts future cash flow as a current cash flow linear function (Farshadfar et al, 2008; Waldron and Jordan, 2010). The following regression is estimated from the company's cross-sectional comparison in company-year.

$$E(CFO_{i,t+1}) = \theta_0 + \theta_1 CFO_{i,t} \tag{2}$$

3. Accrual Based Forecasting Models

In accrual-based forecasting models for predicting cash flows, in addition to current cash flows, accruals will be considered such as changes in accounts receivable and payable, payable taxes, etc…. Accrual-based prediction models including reversal and sophisticated models are described below.

3.1. Simple or Reversal Accrual Model (Accrev)

In this model, it is assumed that cash flows treat random walk and working capital accruals are fully collected or paid in the subsequent period.

$$E(CFO_{i,t+1}) = CFO_{i,t} + \Delta AR_{i,t} - \Delta AP_{i,t} - \Delta ACCEXP_{i,t} - \Delta ACCIT_{i,t} \tag{3}$$

3.2. Sophisticated Accrual Model (Accsoph)

This model adds the end-of-period inventory role as subsequent period sales forecasts to the reversal accrual model and consists of a parametric and accrual regression model.

3.2.1. Accrual Parametrics Model (Accpar)

This model requires an indicator to forecast changes in sales from the period t +1 to t +2.

$$\begin{aligned} E(CFO_{i,t+1}) = {} & CFO_{i,t} + \Delta AR_{i,t} - \Delta AP_{i,t} - \Delta ACCEXP_{i,t} - \Delta ACCIT_{i,t} \\ & + (1-\beta)\Delta INV_{i,t} + \left[\frac{(1-\alpha) - (1-\beta)[(1-\pi)+\lambda]}{\gamma(1-\pi)}\right] INV_{i,t} \\ & - [(1-\alpha) - (1-\beta)[(1-\pi)+\lambda]] S_{i,t} - (1-\beta)\gamma(1-\pi) ESales2_{i,t} \end{aligned} \tag{4}$$

3.2.2. Accrual Regression Model (Accreg)

The accrual regression model (ACCREG) variables are identical to the accrual parametric model (ACCPAR). However, the regression coefficient for each variable is estimated by using the least-squares regression instead of using company-specific parameters (Barth et al, 2001; Yoder, 2006; Cheng etHollie, 2008; Ebaid, 2011). The ability to predict models is estimated by absolute prediction error. In assessing the ability to predict the accrual models, the prediction error is compared to the prediction error generated by the exact cash flow model. Accrual regression model is as follows:

$$E\left(CFO_{i,t+1}\right) = \theta_0 + \theta_1 CFO_{i,t} + \theta_2 \Delta AR_{i,t} + \theta_3 \Delta AP_{i,t} + \theta_4 \Delta ACCEXP_{i,t} + \theta_5 \Delta ACCIT_{i,t} + \theta_6 \Delta INV_{i,t} + \theta_7 INV_{i,t} + \theta_8 S_{i,t} + \theta_9 ESales2_{i,t} \quad (5)$$

4. Analysis Method Using Artificial Neural Networ

A neural network includes simple processing layers called neurons that act in parallel with each other. The first layer is the input layer, which can be statistical parameters or components from the conversion of arithmetic functions. The second layer is an intermediate layer or layers (hidden) that make the network structure. The main task of this layer is to extract classified information from existing data. The final layer or output layer determined based on user expectations. This layer can be identified by one or more processing elements in which its output represents the final formulation. The input layer is connected to one or more of the middle layer and the output layer connected to the intermediate layer, where the answer network plays an output role. In addition, each layer has a weight that reflects the effect of neurons on each other. Estimation parameters (weights) done in accordance with learning laws. Rule learning by recurrence relations, generally expressed as differential equations and the process by which weight matrix, weights connecting the input units to hidden units and connection weights of hidden units to output units and bias vector neural network sets; So that the index error is minimized. In this case, after network learning and functional relationship between inputs and outputs, the network can be used as a model or predict response in accordance with a new input pattern. One of the learning algorithms is the propagation algorithm (Smith, 1993). In this algorithm during the training phase, the network input patterns are provided respectively that each input pattern layer to move forward until an output pattern is calculated. The output model is calculated then compared with the desired pattern and error is determined in the following. The error returned back layer by layer and in each layer necessary reforms carried out on weights (this change on the weights is network learning). This process is repeated many times until the total output error converges towards the minimum. There are two-steps in network performance; learning and remembering and diverse types of artificial neural networks in these two steps are different for the following reasons:

- Neuron model employed;
- Network topology;
- Rule (Learning law) Network;

4.1. Multi-Layer Neuron Model

Figure 1-1, shows the structure of a neuron with an input vector. X is input and Y is the output vector in the model. The effect of X on Y is determined by the scalar value (W). Another input that applied to the network, is fixed 1 in which is multiplied to bias b sentence (and it is the direction of impact to the network from the outside) and then sum with WP. This sum is the network net input which will be available for activation function. Finally, the output neurons would be possible in the form of y=f (WP+b). Trigger function f will be selected by the user depending on the type of response variable (output). Network parameters (W,b) are adjustable due to the choice of F and type of learning algorithm.

4.2. Multi-Input Neuron Model With The Middle Layer (Mlp)

Multiple nodes connected in series and parallel, form a larger and more complete single-layer perceptron network which an example of this is showed in figure 1. In this case, each node of the input vector is related to middle layer individual nodes and associated with the response variable. A single layer perceptron network consists of an input and an output layer. Nude i is also called a neuron, will be presentable as follows. This figure contains a collector and a non-linear function f. X_k inputs (k=1,…,k) accumulate in neurons with Wik_i weights with b_i fixed size collector. As a result, n_i= net_i will be net input of function f. Finally, y_i will be the output of nude i. At the same time, activity function in proportion to output (here quantitative) is considered as (f (u) = (u)) (YousefiRadmandi, 2009).

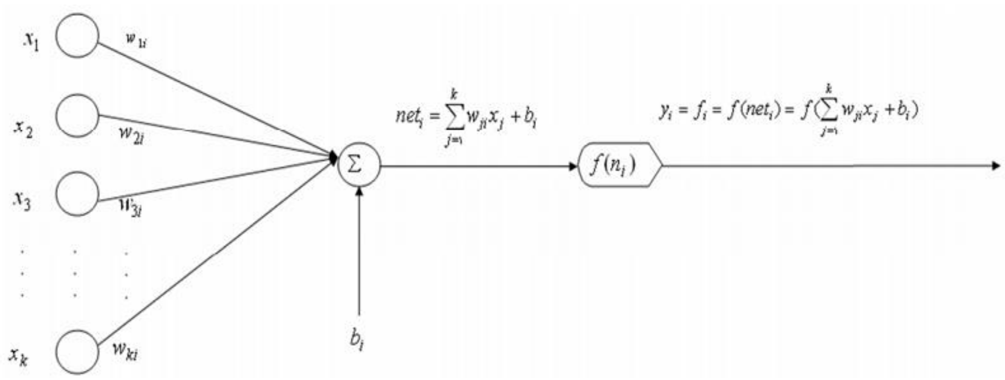

Figure 1. single-layer perceptron with multiple nodes

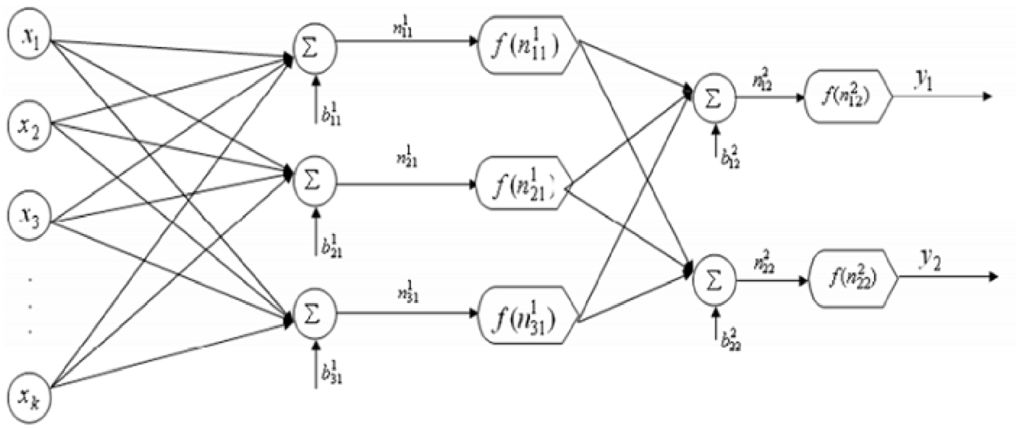

Figure 2. MLP network with a hidden layer

Figure 2, A multilayer perceptron network consists of an input layer, one or more hidden layers and one output layer. In this type of network, a collector and a non-linear drive function called f are available. X_k inputs (k=1,…,k) accumulate in neurons with Wik_i weights with b_i fixed size collector. As a result, a net input network n_i will be available for function f. Finally, the network output y_i is available as follows:

$$y_i = f_i = f(net_i) = f\left(\sum_{i=1}^{3} w_{ji}^2\, f\left(net_{j1}^1\right) + b_{j2}^2\right) =$$
$$f(\sum_{i=1}^{3} w_{ji}^2\, f(\sum_{k=1}^{k} w_{kj}^1\, x_k + b_{j1}^1) + b_{j2}^2) \qquad (6)$$

It should be noted that the trigger function is the same identity function.f (u) = (u) and middle layer neurons are useful when their trigger functions are nonlinear. Central neurons' performance is the interface between input and output vectors and practically, output layer neurons entrance represents the effect of the input vector. The number of middle layers, the more data will be extracted by the network. So with the rise of the middle layer, the neural network will be able to give a better picture of parameters available space (Yousefi Radmandi, 2009).

What is important in the neural network is the appropriate choice of weights and bias network measures if necessary. Choosing weights method is known as learning algorithms. A significant part of network differences is the procedures to set up its parameters. Set up network parameters method is the learning network. Learning systems behavior expressed by the recursive algorithm; that's why these algorithms called learning rules and expressed by differential equations. The process of This algorithm available data so that specified performance index which is usually estimated, optimizes according to network response which is the learning process purpose.

Normally there are two types of learning, supervised and unsupervised learning. In supervised learning assumed that in each learning stage, the learning system desired and the actual answer is already available, but in unsupervised learning desired and the actual answer is not available.

There are various learning algorithms. One of them is the backpropagation error algorithm. In fact, the backpropagation error algorithm is supervised learning. This means that when input applied to the network, network answer compared to target answer, then learn error is calculated and used to configure network parameters; so if next time the same input applied to the network, the output is closer to the target answer. This algorithm is based on delta law using the sum of squared error and suitable for output neurons. There are two ways to implement this algorithm that include batch and sampling methods (Yousefi Radmandi, 2009).

In the batch method, all outputs applied to the network before setting up weights and in sampling method gradient and weights calculate and set each time after each input applied to the network.

It should be noted that in setting parameters of middle and output layers, various activation functions can be used. Depending on the response variable in this study which is quantitative, activation function identification in the output layer and hyperbolic tangent in the middle layer are used to set parameters.

Research Findings

As previously stated, the aim of this study is to select the appropriate model to predict cash flow. The cash flow predicting model can be based on cash or accrual prediction models. In the random walk cash flow forecast model, future cash flows are equal to current cash flows and in the cash regression model, next period's cash flows are predicted as a linear function of current cash flows and then model coefficients are estimated. In simple or inversely accrual models, it is assumed that cash flow is random and current receivables and payables are reversible in subsequent period and can be used to predict cash flows, however, in Sophisticated model, estimating parameters of prediction model due to nonlinearity with response function is not easily feasible and numerical methods are used. In this section, cash flow prediction models are analyzed for achieving goals and responding to hypotheses based on data and also their predictive ability will be examined by the sum of squares error criterion.

1. Testing Hypothesis 1

In order to test the first hypothesis, comparison models are done in two steps: First, simple prediction models (random step and reversal accrual model) and next, sophisticated prediction models (cash regression models, accrual regression models and accrual parametric) will be compared and finally, by general comparison of all simple and sophisticated models, the appropriate model for predicting cash flow will be determined.

1.1. Comparison of Random Walk Prediction and Reversal Model

In order to compare the predictive power of random walk and reversal accrual cash flows prediction models, regression analysis was used and results are presented in Table 3. The mean forecast error was 1.065 and the sum of squared errors was $2.48*10^{26}$ for random walk model while the mean forecast error for reversal accrual cash flows prediction models was 1.195 and the sum of squared prediction errors was $3.97*10^{26}$ for this model. Therefore, the random walk cash flow model in comparison with the reversal accrual model has a less predictive error.

Table 3. Comparison of Random Walk and Reversal Accrual Models

Proper Model	**Random walk**	**Reversal accrual**	**Prediction Error**
Random walk	1.065	1.195	Mean forecast error
Random walk	$2.48*10^{26}$	$3.97*10^{26}$	sum of squared prediction error

1.2.Comparison of Cash Flow Regression and Sophisticated Accrual Prediction Models

By fitting cash flow regression, sophisticated accrual parametric and accrual regression models, Model predictions were evaluated. Sum of squared

The prediction error for the cash flow regression model was $2.25*10^{26}$. This criterion was equal to $2.22*10^{26}$ for sophisticated accrual parametric and $3.78*10^{26}$ for the accrual regression model.

Fitting Cash Flow Regression Model (Cfreg)

In order to fit a cash-flow regression model to predict cash flows for the year 2017 based on linear regression, companies were surveyed in total. Results showed that the sum of squared prediction error in this model for the whole year-companies is $2.25*10^{26}$. Results of analysis variance and regression line coefficients are shown in tables 4 and 5.

Table 4. Variance analysis of fitting 2017 cash flow regression line based on previous period cash flow

Source of change	sum of squares	Degree of freedom	Average of squares	F-Test criterion	P-value
Regression	$4.616*10^{26}$	1	$4.616*10^{26}$	447.703	0.001>
Error	$2.248*10^{26}$	218	$1.031*10^{26}$		
Total	$6.863*10^{26}$	219			

For this model, the coefficient of determination is 0.673. The sum of the squared prediction error for this model is equal $2.25*10^{26}$.

Table 5. Analysis of 2017 coefficients of cash flow regression line based on previous period cash flow

Source of change	sum of squares	standard error	T-Test criterion	P-Value	VIF
Regression Intercept	$3.158*10^{10}$	$7.057*10^{10}$	0.873	0.384	
CFO	0.817	0.039	21.159	0	1

Since the CFO probability value is zero, it can be concluded that CFO is an effective factor in predicting this model. On the other hand, when the sales volatility variable is added to the above model, the numerical value of the criterion factor is changed to 0.729. Also, if the firm size variable is added to the above model, the coefficient of determination numerical value will be increased to 0.772. Therefore, adding these models will improve the variable predictive power.

Sophisticated Accrual Parametric Model Fitting (Accpar)

For fitting this model, due to parameters nonlinear relation with response function, nonlinear regression was used. Results are presented in Tables 6 and 7.

Table 6. Analysis fitting the variance of 2017 sophisticated accrual parametric model non-linear regression

Source of change	sum of squares	Degree of Freedom	Average of squares	coefficient of determination criteria
Regression	$3.773*10^{26}$	5	$7.546*10^{26}$	0.614
Error	$2.219*10^{26}$	159	$1.396*10^{26}$	0
Total	$5.992*10^{26}$	164		

For this model, the coefficient of determination is 0.614 and the sum of squared prediction error is $2.22*10^{26}$.

Table 7. Parameter estimation of 2017 sophisticated accrual parametric model by non-linear regression

Parameter	Estimation	Standard error
Alpha	4.413	37658535/621
Beta	-1.303	0.639
Phi	1.135	661574.131
Landa	3.317	37515033.564
Gama	4.179	20455897.104

Accrual Regression Model Fitting (Accreg)

The analysis performed in this model is based on linear regression models for companies and presented in Tables 8 and 9 as above.

Table 8. Analysis fitting the variance of 2017 accrual regression model

Source of change	sum of squares	Degree of freedom	Average of squares	F-Test criterion	P-value
Regression	$5.376*10^{26}$	8	$6.721*10^{25}$	275.326	0
Error	$2.783*10^{25}$	155	$2.441*10^{23}$		
Total	$5.755*10^{26}$	163			

For this model, the coefficient of determination is 0.934 and the sum of squared prediction error is $2.78*10^{25}$.

Table 9. Accrual regression coefficient analysis for 2017

Source of change	sum of squares	standard error	T-Test criterion	P-Value	VIF
Regression Intercept	$-1.152*10^{11}$	$4.354*10^{10}$	-2.647	0.009	
CFO	1.186	0.065	18.126	0	1.661
ΔAR	0.021	0.055	0.375	0.708	1.624
ΔINV	0.22	0.354	0.623	0.534	2.036
ΔAP	-1.897	0.15	-12.659	0	2.553
ΔACCIT	-1.818	1.367	-1.33	0.185	1.303
ΔSales	-0.123	0.097	-1.266	0.207	2.08
S	0.084	0.022	3.763	0	3.015
Inv	0.351	0.101	3.48	0.001	2.696

When the firm size variable is added to the above model, the coefficient of determination numerical value will be increased to 0.934. It means adding a firm size variable will not change accrual models predictability.

1.3.Comparison of Simple and Sophisticated Models

Based on the results obtained from complex models including regression models, both linear and nonlinear, the selected model can be specified for the sample group of companies. According to Table 10, the accrual regression model is an appropriate model for predicting cash flows in Iranian companies.

Table 10, Comparison of Linear and Nonlinear Regression Models to Predict Cash Flow

Criterion Model	sum of squared errors of prediction	Coefficient of Determination
Cash flow regression model (liner)	$2.25*10^{26}$	0.673
Accrual parametric model (non-liner regression)	$2.22*10^{26}$	0.614
Accrual regression model (liner)	$3.78*10^{25}$	0.934
Proper model	Accrual regression	Accrual regression

By comparing Table 10 and Table 3 a suitable model for predicting cash flow in Iranian companies can be recommended. Selecting a proper model based on Sum of squared prediction error is presented in Table 11.

Table 11. Choosing a proper model based on the sum of squared prediction errors

Hypothesis	Model		value Criterion	Primer Choice	Final Choice
one	Simple	Random walk	$2.48*10^{26}$	Random walk	Accrual Regression
		Reversal accrual	$3.97*10^{26}$		
	Sophisticate	Cash Flow Regression	$2.25*10^{26}$	Accrual Regression	
		Accrual Parametric	$2.22*10^{26}$		
		Accrual Regression	$3.78*10^{25}$		

2.Investigating the Relationship Between Cash Flows Forecasting Models and Corporate Characteristics

Spearman correlation coefficient test was used to investigate the relationship between accruals and cash models prediction with the variability of ending inventory ratio, sales, and profit volatility and firm size. The results are presented in Table 12.

Table 12. Investigation of the Relationship between Cash Flow and Accrual Models in 2017 with the Companies characteristics

Model Variables	Sales	Firm Size	variability of inventory	variability of profits	Sales volatility
Random walk Model Correlation Coefficient P-Value N	**0.651 0 220	**0.662 0 164	0.030 0.704 160	0.14 0.857 164	**0.234 0.001 196
Reversal accrual Model Correlation Coefficient P-Value N	-0.053 0.504 164	**0.635 0 187	-0.070 0.380 160	-0.040 0.608 164	-0.013 0.867 164
Cash Flow Regression Model Correlation Coefficient P-Value N	**0.65 0 245	**0.662 0 164	0.003 0.969 160	0.019 0.799 185	**0.519 0 221
Accrual regression model Correlation Coefficient P-Value N	**0.768 0 187	**0.757 0 187	0.019 0.813 160	0.019 0.795 185	**0.823 0 187
Accrual parametric model Correlation Coefficient P-Value N	*0.762 0 187	**0.762 0 187	0.005 0.945 160	0.023 0.759 185	**0.707 0 187
** significant at 0.01 level					

Relationship between the whole company's characteristics and cash flow forecasting models based on the above table with less than 0.05 probability value, can be summarized as follows:
1) There is no significant relationship between inventory turnover ratio and model prediction for future cash flow.

2) There is no positive relationship between Sales volatility and accrual reverse model, but there is a positive relationship with other models.

For instance, the maximum relationship is related to the accrual regression model, which means as sales volatility increases this model prediction will increase compared to other models.
1) In earnings variability, there is no significant relationship between this feature and the above models' prediction.
2) Infirm size, the most correlation is with predicting cash flows are based on accrual parametric model (0.762).

3. Fifth and Sixth Hypotheses Examination

To predict by using an artificial neural network model, a three-layer Perceptron Neural Network with the following specifications were used:

- input layer with 9 neurons, middle layer with 6 to 20and output layer with one neuron
- Activation function used in the middle layer: the hyperbolic tangent
- Activation function used in output layer: identity function
- Learning rate 0.4, 0.35, 0.3, 0.25, 0.2, 0.15, 0.1, 0.05 and Momentum 0.9, 0.8 and 0.8 were considered.
- Training/Learning: random selection of approximately 70 percent of data
- Test set: other remaining data
- Decision criteria for learning: the sum of squared prediction error.
- Decision criteria to select the best network structure: the sum of squared prediction error.
- Choose the most influential variables in forecasting: Penetration strategy variables.

Neural network models based on the above specifications consist of 360 models within 15 structures (24 models for each structure) fitted and the best model in each structure was reported in table 13. From these fifteen structures, the best model to predict with 8 and 11 hidden nodes were concluded.

Table 13. Choose the best network structure to predict

Experimental phase		Training phase		
Relative error	Total square error	Relative error	Total square error	Number of hidden nodes
0.833	91.54	0.574	157.23	6
0.687	25.22	0.545	143.6	7
0.342	17.56	0.407	113.26	8
0.55	31.1	0.667	175.45	9
0.744	22.8	0.626	166.76	10
0.447	96.36	0.445	120.42	11
0.505	15.25	0.627	165.11	12
0.619	137.41	0.576	150.95	13
0.621	189.93	0.664	173.28	14
0.638	45.81	0.568	153.81	15
0.477	55.4	0.683	183.42	16
0.833	109.52	0.652	179.42	17
0.639	21.32	0.61	164.77	18
0.929	86.33	0.816	227.32	19
0.928	26.91	0.693	187.47	20

As shown in table 13, according to results during the training phase, a network with 8 and 11 hidden nodes offered the best prediction and prediction result was also reported in the experimental phase. Variables affect embellishment for these two networks was obtained as follows:

Table 14. Variables effect embellishment on prediction with 8 hidden nodes model

Variable	Penetration rate	standard penetration rate
S	0.227	1
CFO	0.21	0.93
delta-INV	0.134	0.59
delta-AP	0.125	0.55
delta-AR	0.96	0.42
delta-Sales	0.94	0.41
delta-ACCIT	0.76	0.33
Inv	0.25	0.11
Gover	0.14	0.06

Given the penetration rates of S.CFO, ΔINV, ΔAP are more than 1, they have the most impacts but ΔAR and Δsales are close to 1 and have an influence on forecasts based on 8 hidden nodes model.

Table 15. Variables effect embellishment on prediction with 11 hidden nodes model

Variable	Penetration rate	standard penetration rate
S	0.327	1
CFO	0.153	0.47
delta-INV	0.143	0.44
delta-AP	0.101	0.31
delta-AR	0.091	0.28
delta-Sales	0.074	0.23
delta-ACCIT	0.054	0.17
Inv	0.046	0.14
Gover	0.01	0.03

As shown in table 15, forecasts based on the model with 11 hidden nodes, CFO with a penetration rate of 0.327 has the most effect but S, ΔAP, ΔACCIT, and ΔAR variables, respectively, have greater influence compared to other variables.

Research Findings

This research, based on subject literature, focuses on the importance of forecasting cash flows and accrual and cash items conditions. Afterward, in order to compare different models and select the appropriate model, the sum of squared prediction errors was used. Also, by fitting different artificial neural network models, the best prediction model and variables affect embellishment reported in two structures.

The first hypothesis was put forward in response to the first question "whether cash flow prediction based on accrual models is better than cash models?" and in order to prove this claim, three main themes including cash, accrual and cash and accrual models comparison were used which is compatible with past studies like Bareth et al, 2001; Al-Attar et Hussain, 2004; Chotkunakitti, 2005; Habib, 2010; Ebaid, 2011; Francis et al, 2012; Saghafi and Fadaie, 2007; Mahdavi and Saberi, 2010. cash models analysis results indicate that cash flow regression model has less prediction error than random walk model; In the analysis of accrual models consist of simple and sophisticated models, multiple regression, linear and nonlinear regression were used; Findings show that accrual regression model is more appropriate than other accrual models with regard to coefficient of determination and sum of squared prediction error. Finally, results from comparing accrual and cash models showed that linear regression model with error $3.78*10^{25}$ has less prediction error (cash flow regression model with error $2.25*10^{25}$) and is more suitable for forecasting cash flows compared to cash models in firms accepted in Tehran Stock Exchange; So, the first hypothesis is confirmed.

The second hypothesis testing results in order to answer the second question "the ability to predict accrual models in comparison with cash flow models will decrease with changes in ending inventory to future sales ratio" showed that contrary to Yoder's research (2006), there is no significant relationship between inventory turnover to futures sales and cash flow forecasts based on various models in the hypothesis. The lack of economic stability can be justified by this outcome. Lack of economic stability is one of the most important components affect economic activities. Economic stability means stable, reliable and predictable conditions for economic activities. Under instability conditions, forecasting models will be basically problematic. Among economic instability indicators, inflation fluctuations, which have been clearly seen in recent years in Iran, have led to inefficiencies in models.

In the third hypothesis, the effect of sales and profit volatility on accrual models in comparison with cash flow models was tested and results showed that accrual models predictability does not change in comparison with cash flow models in the variability of profits but while sales volatility increases accrual models predictability compared to cash flow models. Results indicate that the greatest relationship is between this feature and the accrual regression model. It means the more sales variability is accrual regression model ability will also increase (Yoder, 2006).

According to the fourth hypothesis, we conclude that in firm size, accrual models ability is more consistent than cash flow models; results show that the greatest relationship between this feature is with accrual parametric model which is compatible with Lorek et Willinger (2008) research results. Therefore, it can be said that in Iranian companies, accrual regression models are more efficient and some features such as firm size are more functional on the effectiveness of these models.

Results of the fifth hypothesis testing showed that multilayer perceptron neural network is a suitable model for predicting cash flow and according to previous research findings based on multi-variable linear regression model superiority in the fifth and sixth hypotheses, nine fundamental accounting variables were considered as network inputs and found on variables influence strategy, result of various network models fitting indicated that two structures with 8 and 11 hidden nodes are the best prediction models; and variables arrangement to predict cash flow in different structures requires appropriate software design which has been suggested in suggestions. In addition, in relation to the fourth main hypothesis, results showed that being a government-owned company with penetration coefficients of 0.6 and 0.3 did not have a significant impact on cash flow projections. Therefore, it can be stated that the sixth hypothesis is rejected.

Based on the results of this paper, creditors evaluations in customers' ability to generate cash flows, investors to cash flow prediction in business units and managers in various decision makings that require cash flow estimations as well as analysts in interpreting and helping users, could benefit from this research results. According to these findings, suggestions are presented as follows:

1) Our criterion in this study was the average total assets in relation to the firm size variable. It is suggested that in the next researches, the logarithm of average total assets [ln (TA)] or the logarithm of current sales to future sales ratio ln (s_t/s_{t+1}) be used as a measure of firm size.
2) A survey and estimation of the overall cash flow forecasting model by using panel analysis that has not been used in this study due to lack of information.
3) breakdown of sample companies according to industry type and studying the appropriate model for each of them, which in this study was not possible due to lack of information and the low number of companies.
4) It is recommended that in future investigations probable networks, whose structure generally includes one input and three information-processing layers (pattern layer, classification, and output layer) used and compared to the results of this paper.
5) Since predicting cash flow is a multifaceted approach, it is convenient that other approaches be investigated, too.
6) Regarding company characteristics impact on cash flow forecasting; just a small number of company characteristics were reviewed. It is recommended that future researches include other features like [ln (Stock Price_t/Stock Price_{t+1}) SR, lns.

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