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Developing a Grey Wolf Optimization-Based Gray Box Model for Cash Flow Forecasting: A Study on Tehran Stock Exchange Companies

Ahmad Ahmadi*

Department of Accounting, Islamic Azad University
Birjand Branch, Birjand, Iran
ad_ahmadi@yahoo.com

Farzaneh Nasirzadeh

Department of Accounting
Ferdowsi University of Mashhad, Mashhad, Iran
nasirzadeh@um.ac.ir

Esmaeil Hadavandi

Department of Industrial Engineering
Birjand University of Technology, Birjand, Iran
es.hadavandi@gmail.com

Mohammad Chavosh Nejad

Department of Materials and Production
Aalborg University, Denmark
mohammadcn@mp.aau.dk

Arash Ghorbani

Department of Accounting, Islamic Azad University
Bojnourd Branch, Bojnourd, Iran
arash.ghorbani.acc@gmail.com

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Cash flow forecasting is a critical aspect of financial planning and has long been of interest to investors and creditors. The Gray Box (GB) method is a widely used tool for forecasting, but a significant challenge in developing a grey box model is parameter estimation. In this study, we introduce a novel approach to cash flow forecasting called the Grey Wolf Optimization-based Grey Box model (GWOGB). The GWOGB employs a GWO algorithm as a global search method to determine the parameters of the GB model.

*Corresponding author.

To enhance the accuracy of future cash flow forecasting, we incorporate firm-level control variables as well as market and financial control variables into the classical model. To evaluate the performance of the proposed model, we use a sample of 250 firms listed on the Tehran Stock Exchange. Our empirical findings indicate that the GWOGB outperforms the generalized method of moments (GMM). Additionally, we employ sensitivity analysis to discern the source of forecast error and find that the inclusion of the nonlinear effect of sales growth rate on working capital accruals and future cash flow significantly reduces forecast error. The results show that using a nonlinear form of the GWOGB model is a promising approach for modeling the complex relationships between cash flow and working capital accruals.

Keywords: Cash flow forecast; generalized method of moments; gray box method; gray wolf algorithm; sensitivity analysis.

1. Introduction

The annual financial statements of a firm typically contain the most important financial information about the company. Financial analysts extract information from these statements to make decisions such as equity valuation and bond rating. From the disclosed accounting numbers available to the public, readers can form their views about a firm's prospects. Profitability, which is the foundation upon which a firm exists, is the most important property of interest to financial analysts and other users who have reasonable rights to the financial information of the firm. Financial analysts use their knowledge and proprietary methods to make a 'correct' judgment about the financial information published by the firm. Investors price a firm and trade its equity in the stock market based on their expectations regarding the firm's future profits, which are reflected in the share price. The value of a firm is often considered as the aggregation of discounted cash flows it will receive in its lifetime. Therefore, for commonly used valuation methods, such as multiples and discounted cash flow methods, the primary input is the estimated cash flow. Operating cash flows represent the amount of cash that a company generates or utilizes through its core business operations during a specific period, typically a quarter or a year. These cash flows are a crucial measure of a company's financial health, as they reflect the actual cash inflows and outflows from daily operations, including sales, expenses, and investments in working capital. Positive operating cash flows indicate that a company is generating enough cash from primary business activities to cover expenditures and invest in operations, while negative operating cash flows may indicate that a company is facing difficulty in generating sufficient cash to maintain its business. Investors and analysts frequently employ operating cash flow as a key metric to evaluate a company's financial performance and assess its capacity to produce cash in the future.

Market participants are always interested in earnings and cash flow forecasts as criteria for performance appraisal. Short-term cash flow forecasting evaluates daily activities, whereas long-term forecasting is conducive to assessing the company's survival and stock value. The literature on forecasting has described the advantages and drawbacks of modeling these two important accounting variables. In the annual financial statements of firms, the values for earnings and cash are not necessarily equal due to the effect of accruals. Moreover, the type of operating cycle and the stability or instability of the firm's situation affect its cash flow and earnings. While earnings are a more accurate measure than cash flow for forecasting future earnings, cash flow is less likely to be manipulated compared to earnings due to the effects of accruals. Therefore, incorporating both cash flow and earnings measures in a financial analysis process provides more comprehensive information than analyzing them separately, enabling investors and analysts to make informed decisions.

However, univariate models used to forecast earnings may not be suitable for forecasting future operating cash flow due to the varying effects of accruals on cash flow in future periods. Other accounting variables containing more information about operating cash flow should not be neglected. The authors of 1 and 2 showed that cash flow can be more accurately forecasted using lagged values and accruals. The level, quantity, and quality of accruals also influence the performance of forecasting models. In this sense, operating cash forecasting is more complex and convoluted than accruals. So far, little effort has been made to explore the time series properties of cash flow, and there are no precise and generalizable results on this subject.[3]

Liquidity is a critical factor in assessing the economic status of a firm, and cash flow is a crucial measure of liquidity. Therefore, for beneficiaries, stakeholders, and investors, accurate cash flow forecasting is of utmost importance. A reliable cash flow forecasting model with minimum errors that account for variables not typically considered in the forecasting process can provide a more precise forecast of cash flow. By using advanced statistical techniques to control nonlinear effects and identify the most relevant variables affecting cash flow forecasting accuracy, financial analysts can develop more accurate forecasting models.

Linear models, such as multivariate linear regression models, are the most commonly used cash flow forecasting techniques.[4] However, there are at least three limitations regarding the linear models developed for operating cash flow forecasting that have not been adequately considered in previous studies. The first limitation is the lack of diversity in the proposed models. Although several criteria have been proposed for forecasting operating cash flow, they tend to disregard the specific properties of each company. Given the diverse structure and management approaches of different companies, it is necessary to consider heterogeneity in operating cash flow forecasting models. The second limitation is the dynamic features of the operational cash forecasting process. Organizations go through various periods with specific conditions during their life cycle. The type and structure of the industry, as well as the economic and political conditions of the countries in which they operate, can also influence their performance. Therefore, a static model cannot provide an accurate forecast of future cash flow. Instead, a dynamic model that considers the changing conditions of a company and its environment is needed. The third limitation is achieving an exhaustive model. Given the diversity of market economic conditions and the structure of companies, it is challenging to develop a model that is comprehensive enough to cover all dynamic aspects. Therefore, it is important to identify the most critical factors affecting a company's cash flow and develop models focusing on them.

The Grey Box (GB) method is one of the most widely used techniques for forecasting problems.[3] Estimating the parameters of the GB model is a complex issue that can be viewed as an optimization problem. In this paper, we use the Grey Wolf algorithm as a powerful optimization method[5] to estimate the parameters of GB and propose a Grey Wolf Optimization-based grey-box model (GWOGB). Additionally, by using the Sensitivity Analysis Method (SMA), we examine the source of forecast error in the operational cash flow. The analytical approaches and research design used in this paper show some resemblance to the work published by Ref. 6, demonstrating the use of comparable methodologies to tackle problems in different domains.[6]

The main goal of this study is to identify the source of cash flow forecasting error that has not been explicitly addressed in previous studies.

This paper is arranged as follows. Section 2 provides a literature review. Section 3 discusses the research methodology and sample selection process. Section 4 presents the results. Section 5 contains the discussion. Section 6 concludes.

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2. Literature Review

2.1. *Cash flow forecasting challenges and influential variables*

Prior studies have proposed a variety of cash flow forecasting models. However, despite the bulk of research on cash flow forecasting, selecting the best model and customizing it for different problems requires specific investigation. Much of the research in cash flow forecasting is based on the claims made by the Financial Accounting Standards Board (FASB). The Board states that the ability to forecast future cash flow is the first and primary goal of financial reporting. According to FASB (1978), in forecasting future operating cash, accrual components of earnings are more effective than cash flow.

Many researchers have concluded that earnings and cash play an essential role in forecasting future operating cash flow, but studies in this area are contradictory.[7] Some studies offer evidence that supports the FASB claim regarding the superiority of accrual components of earnings over current operating cash flow in forecasting future cash flow.[8,9] On the contrary, other studies suggest that earnings have weak performance in forecasting future operating cash flow, while operating cash flow and its components can forecast future operating cash flow more effectively.[10] Ebaid[11] used cash flow prediction models to examine the predictive abilities of earnings and cash flows for future cash flows. The study's findings show that aggregate earnings have a superior predictive ability than cash flows for future cash flow forecasting. Nam *et al.*[12] found that, on average, accruals improve upon current cash flow from operations (CFO) in predicting future cash flows. Barth *et al.*[13]

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revealed that partitioning accruals based on their role in cash-flow alignment would increase their ability to forecast future cash flows and earnings. Chen *et al.*[14] recommended that researchers avoid using surrogate measures of cash flows, such as earnings and its components. Khansalar and Namazi[15] investigated the incremental information content of estimates of cash flow components in predicting future cash flows and found that around 60% of a current year's cash flow will persist into the next period's cash flows. Nallareddy *et al.*[7] found that cash flows are superior to earnings in predicting future cash flows.

Despite these discrepancies in the results, changes in accounting over time have highlighted the importance of cash flow forecasting. According to Ref. 7, the conflicting results in previous studies are primarily due to the difference in evaluating accruals and cash flow. The ability of earnings and current cash flow to forecast future cash flow has increased over time, but this improvement in predicting the current cash flow has been far more significant than earnings. Nallareddy *et al.*[7] describe the reasons for the discrepancy in results of previous studies as the difference in measurement method (measurement criteria based on the balance sheet or earnings statement), differences in selected periods, and sampling methods used in previous research works, differences in definition and measurement of variables, and differences in estimation methods (cross-sectional, time series or panel).

Incorporating new variables that influence future cash flow can boost the capability of forecasting models. In order to increase the predictability of cash flow, the operational characteristics of companies can be used. Adding these variables to the cash flow forecasting model can amplify predictability.[3]

If companies are heterogeneous, predictive models will not be able to discover this heterogeneity, and the results tend to be less accurate. The heterogeneity could be attributed to the type, operational structure, and differences in the sales growth rate of companies. Allen *et al.*[16] divided working capital accruals into good accruals and accrual estimation errors. Good accruals are obtained entirely from firm operations and will be converted into cash in future periods. The components of good accruals are accruals related to sales growth and employee growth variables, and lagged, current, and future cash flows. Managers and investors cannot access all the information about accruals at the time t. Hence, if a systematic relationship can be established between accruals at time t and cash flow at time $t+1$, it can be inferred that accruals are a favorable criterion for forecasting the future. Therefore, by dividing accruals into accruals related to operations growth and accruals related to cash flows, future cash flows can be predicted with greater precision.

Another variable affecting future cash flow forecasts is financial leverage.[17] Financial leverage is crucial to shaping a company's cash policies. Companies can utilize borrowing as an alternative to preserving cash. Besides, companies can maintain their financial flexibility through large cash reserves or unused debt capacity (low leverage). Leveraged companies retain more cash to mitigate financial risk. The financial leverage ratio is a factor in determining a firm's ability to issue new debt securities. If a firm can repay financing costs, its financial flexibility will be high, and it may preserve less cash flow. For this reason, the relationship between financial leverage and the future cash forecast cannot be accurately explained. Therefore, investigating the financial leverage variable in predicting future operating cash flow may yield new results.

From another perspective, a country's economic and political conditions can also influence the predictability of the future cash flow of companies. Factors such as financial and economic sanctions, business cycles, and exchange rate fluctuations — especially in recent years — have significantly impacted firms' cash flow forecasting ability; therefore, including these variables in the forecasting model can amplify its efficiency and accuracy.

In conclusion, the effectiveness of various cash flow forecasting models is still under investigation, as previous studies have reported conflicting results depending on the measurement method, selected periods, sampling methods, definition and measurement of variables, and utilized estimation methods. However, incorporating additional variables such as operational characteristics, financial leverage, and economic and political conditions has been shown to improve the capability of forecasting models. Furthermore, the heterogeneity of companies and the components of good accruals are important factors that affect future cash flow forecasts. As the complexity of business operations and financial instruments continues to grow, the development of more advanced forecasting models and tools will play an increasingly important role in the future of financial management.

2.2. *Forecasting future cash flow by analysis of forecast error*

One of the main goals of this study is to identify the source of cash flow forecasting errors. For this purpose, in this section, several previous studies are stated, and the origin of their prediction error is explained. As an innovative approach to the problem, this research attempts to identify the source of prediction error that has not been investigated so far and to provide a model with the lowest prediction error.

Lorek and Willinger[18] used four seasonal autocorrelation models (SAR), seasonal moving average (SMA), Wilson multivariate cross-sectional regression, and a multivariate time series regression model to forecast future operating cash flow. They aimed to identify a model for more accurate future cash flow forecasting. SAR models and SMA only used seasonal lagged cash flow as a predictor variable. In Wilson's cross-sectional regression, a wide range of variables, including current and lagged sales, net profit, operating cash flow, current and non-current accruals, and capital expenditures, served as predictors of cash flow. However, among these models, the multivariate time series regression model, which consisted of the variables of lagged cash flow, delayed operating earnings, and accruals components, estimated the lowest operating cash flow forecast error. Compared to other models, using different variables in this model reduced the prediction error. The source of forecast error in this study can be attributed to changes in independent variables in the prediction model.[18]

Bart *et al.*[2] expanded the model proposed by Ref. 2 to develop a new model for operating cash flow forecasting. Their main argument revolved around the fact that earnings, rather than being a direct predictor of operating cash flow, should be broken into its components. This is because each component can have varying effects on the forecast of future operating cash flow. They contended that the source of operating cash flow forecast error is the failure to consider earnings components in the forecast model, and their inclusion could reduce the forecast error in the model.[2]

Brochet *et al.*[19] adopted a method comparable to that of Ref. 2 to forecast future operating cash flow. Their results indicated that the operating cash flow forecast error is significantly reduced by breaking accruals into components. Besides, they found that the positive accruals in the model have stronger operating cash flow predictability than the simple cash flow. Also, when there are fluctuations in cash flow, the predictability of accruals improves. In addition, the presence of discretionary accruals in the accruals structure undermines its predictability. Therefore, the source of forecast error can be the type and structure of accruals.[19]

Farshadfar *et al.*[10] predicted future cash flow based on four criteria: lagged earnings, lagged earnings plus depreciation, working capital, and lagged cash flow. Their results illustrated that forecasting future operating cash flow using current cash flow was more accurate and less risky than the other three criteria. They also investigated the effect of firm size on operating cash flow forecasting, concluding that operating cash flow forecasting errors were lower in corporations. Therefore, considering the operational variables of the company in the model can influence the forecast error.[10]

Orpurt and Zang[20] suggested that drafting a cash flow statement, and its direct (rather than indirect) calculation not only has a positive effect on the predictability of operational cash flow but also is more informative. They proposed the concept of correlation error of financial statements to be added to the forecasting model. The correlation error of the financial statements describes how the estimated operating cash flow and the balance sheet, earnings, and loss figures are different from directly calculated operating cash flow. In their study, operating cash flow was estimated once based on its direct components and then on the indirect method, and these components were incorporated into two separate models. Their results demonstrated a broad correlation error for calculating cash flow using the indirect method, while the error decreased in the direct method. Based on these findings, different methods of cash flow estimation and failure to consider the correlation error in financial statements were introduced as the source of forecast error.[20]

According to Ref. 13, investors shape their expectations about the economic factors of future periods, which leads to cash flow generation to forecast operating cash flow. In operating cash flow forecasting models that contain accruals components, each component has a distinct coefficient and weight with varying levels of effectiveness in operating cash flow forecasting. This is because each component contains specific information about future operating cash flows and is associated with some errors in the forecasting process. Therefore, the results of this study reveal that the source of operational cash flow forecast error is ambiguity surrounding the future and the association of each accrual item with future economic realities.

In another study, Farshadfar and Monem[21] broke down accruals into operating accruals, investment, and financing to forecast operating cash flow. They posited that this classification increases the information content of accruals. Accordingly, they evaluated the relative importance of working capital accruals, non-current operating accruals, and financing accruals in the operating cash flow forecast. The results revealed that working capital and non-current operating accruals had a superior performance in forecasting operating cash flow. In contrast, the role of financing accruals in the forecasting process was insignificant. They divided working capital accruals, non-current operating accruals, and financing accruals into assets and debts components to identify the source of their explanatory power in the operating cash flow forecasting process. The results exhibited that accrual assets have greater explanatory power than accrued liabilities in forecasting the operating cash flow.[21]

Zhu *et al.*[22] utilized an improved genetic algorithm-based Backpropagation neural network model to predict enterprises' free cash flow. The authors used G Company's data to evaluate the optimal number of neurons and population and relative error through data preprocessing, genetic algorithm, and neural network parameter selection. The experimental results indicated that the model's error is the smallest and its prediction ability is the best when the population is 30 and the number of hidden layer neurons is 15. By computing the relative error, they found that the model has a high level of precision in predicting free cash flow. The comparison of the average relative error of relevant forecasting models demonstrated that the model proposed in this paper possesses superior forecasting ability and effectiveness.[22]

Ball and Nikolaev[23] contributed new evidence to the long-standing debate over the value of accounting earnings in predicting an enterprise's future operating cash flows. They found that operating earnings variables, which incorporate working capital accruals, dominate operating cash flows in predicting future cash flows, across multiple forecasting approaches and firm heterogeneity levels. The results suggested that operating cash flows are a noisy measure of operating earnings, and accruals improve their predictive ability. The study challenged the common belief that operating cash flows are superior to earnings in predicting future cash flows and highlights the importance of addressing firm heterogeneity in cross-sectional research designs. The authors concluded that accrual-based earnings measures provide a better basis for predicting future cash flows, consistent with existing academic and practitioner literature.[23]

Furthermore, working capital accruals also significantly impact future cash flow. Therefore, the breakdown of accruals into these components diminishes operating cash flow forecast error. The researchers argued that each component of accruals in operating cash flow forecasting contains diverse information. Therefore, the breakdown of accruals into additional components has provided a more accurate forecast of operating cash flow. They also assessed their results concerning the industry, operating cycle period, asset turnover period, profitability, and company size, concluding that companies' characteristics and operating structure can also influence operational cash flow forecasting. As indicated by the results of this study, the primary source of forecasting error and its superiority over previous studies lies in the fact that it considers more components of accruals affecting the forecast of operating cash flow and also controls the specific characteristics of companies.

Pornupatham *et al.*[24] leveraged the comparative advantages of experimental methods to investigate how investors process information presented in different cash flow statement formats, particularly in the context of various non-recurring items. Their study sheds light on how these presentation methods influence cash flow forecasts. They predicted and found that the indirect method leads to lower forecast errors when non-recurring accrued expenses are present. This finding aligns with the notion that investors activate their existing knowledge structures of operating cash flows based on accruals (rather than cash) in such situations. Conversely, the presence of non-recurring cash flow items or non-recurring accrued revenues does not significantly impact the difference in forecast errors between the indirect and direct methods. This suggests that investors can effectively handle these types of non-recurring items in either presentation format. Finally, the study demonstrated that while the combined direct-plus-indirect method reduces forecast errors compared to the direct method alone, it does not offer any additional benefit for forecast accuracy beyond the indirect method.[24]

In Table 1, the sources of cash flow forecasting errors in previous papers are presented.

In previous studies, modifying the model structure was not explored as a means to improve the prediction of operating cash flow. In this study, in addition to the methods mentioned earlier, the model structure has been adapted to enable more precise operating cash flow prediction. This offers valuable insights into enhancing the accuracy of cash flow forecasting, emphasizing the significance of integrating new variables and adjusting the model structure. By identifying the source of cash flow forecasting errors and proposing a model with the lowest prediction error, this paper fills a research gap and contributes to the existing literature on cash flow forecasting.

3. Research Method

3.1. *Developing the forecasting model*

In this study, an integrated approach was proposed to develop the GWOGB model to forecast the future cash in companies listed on the Tehran Stock Exchange (Fig. 1). In the first stage, we use Barth, Cram, and Nelson model (BCN)[2] as

Table 1. The sources of cash flow forecasting error in previous papers.

References	Dependent variable	Independent variables	Sources of cash flow forecasting error		
			Change in independent variables	Change in cash flow calculation method	Change in the estimation method
Lorek and Willinger[18]	Future operating cash flow	Current Operating Cash Flow, Operating Income, Receivables, Inventory, Account Payables	√		
Bart, Kram, and Nelson[2]	Future operating cash flow	Current Operating Cash Flow, Changes in Receivables, Changes in Inventory, Changes in Payables	√		
Brochet *et al.*[19]	Future operating cash flow	Components of Liabilities and Accrual Liabilities, Discretionary and Non-discretionary Accrual Liabilities	√		
Farshadfar *et al.*[10]	Future operating cash flow	Accrual Income, Accrual Income plus Depreciation, Operating Working Capital, Current Cash Flow, Company Size	√		√
Orpurt and Zhang[20]	Future operating cash flow	Current Operating Cash Inflows and Outflows, Taxes and Interest Paid, Correlation Error Variable in Financial Statements	√	√	
Bart *et al.*[13]	Future operating cash flow	Current Operating Cash Flow and Components of Liabilities	√		
Farshadfar and Monem[21]	Future operating cash flow	Current Cash Flow, Operating Working Capital, Non-current Operating Liabilities, Financing Liabilities, and Operational Variables of Companies	√		
Zhu *et al.*[22]	Future free cash flow	Current free cash flow			√
Ball and Nikolaev[23]	Future operating cash flow	Working capital accruals	√		
Pornupatham *et al.*[24]	Future operating cash flow	Non-recurring accrued expenses		√	

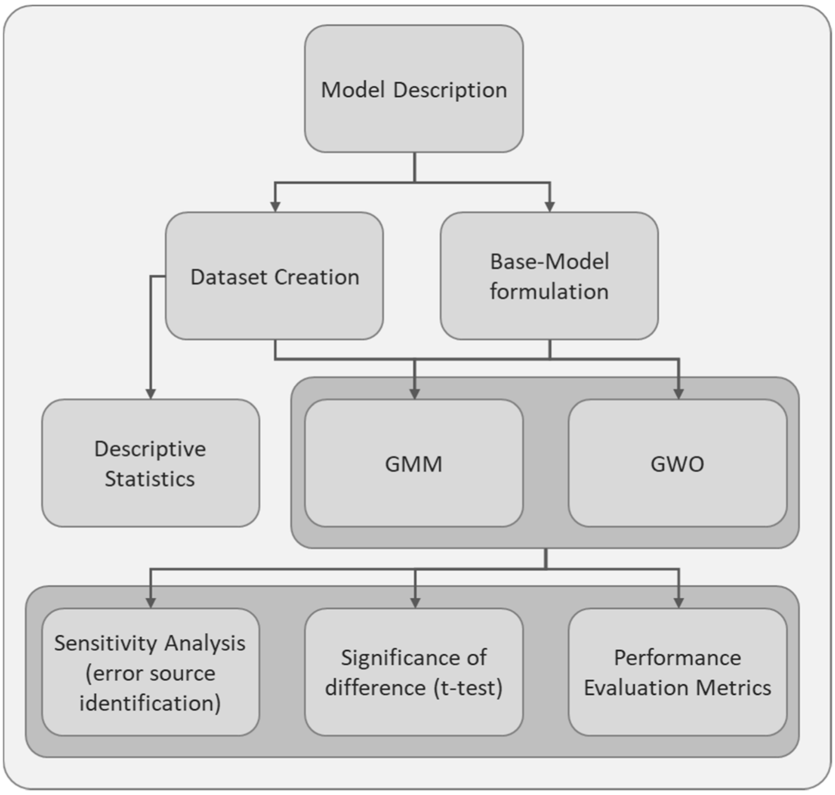

Fig. 1. Model description.

the basic model (Eq. (1)) and propose a new forecasting model.

$$\begin{aligned}\mathrm{CF}_{t+1} = \beta_0 &+ \beta_1\mathrm{CF}_t + \beta_2\Delta\mathrm{Inv}_t + \beta_3\Delta\mathrm{AP}_t + \beta_4\Delta\mathrm{AR}_t + \beta_5\mathrm{Other}_t\\ &+ \beta_6\mathrm{DepAmort}_t + \varepsilon_{t+1}. \end{aligned} \tag{1}$$

In Eq. (1), adding variables affecting the process of forecasting operational cash flow can increase forecasting accuracy. Hence, market and economy-based operational variables were added to this model:

$$\begin{aligned}\mathrm{CF}_{it+1} = \beta_0 &+ \beta_1\mathrm{CF}_{it} + \beta_2\Delta\mathrm{Inv}_{it} + \beta_3\Delta\mathrm{AP}_{it} + \beta_4\Delta\mathrm{AR}_{it} + \beta_5\mathrm{Other}_{it}\\ &+ \beta_6\mathrm{DepAmort}_{it} + \beta_7\mathrm{Lev}_{it} + \beta_8 r_{it} + \beta_9\mathrm{Buscycle}_{it} + \beta_{10}\mathrm{CurVol}_t\\ &+ \beta_{11}\mathrm{Sanc}_t + \varepsilon_{it+1}, \end{aligned} \tag{2}$$

where CF is Cash flow from the operation, ΔInv is the change in inventory during the period, ΔAP is the change in accounts payable during the period, ΔAR is the change in accounts receivable during the period, Other is other accruals, Lev is financial leverage (ratio of total debts to total assets), DepAmort is depreciation and amortization, r is the sales growth rate, and Buscycle is an indicator variable for Business cycles. We used the Hodrick–Prescott filter to identify the regular time series of all sample firms and their boom and recession periods. The filter produces positive output for boom periods and negative output for recession periods. In the end, to achieve the business cycle variable, we assigned 1 and 0 values to boom and recession periods, respectively. CurVol is Exchange rate fluctuation, the rate of oscillation in the USD exchange rate at time t, which is equal to the USD exchange rate to the Iranian Rial at time t divided by the same rate at time $t-1$ and Sanc is an indicator variable for Financial and economic sanctions. This variable received a value of 1 for the 2011–2014 periods (the heyday of sanctions) and 0 for other years covered in the research.

Since including a lagged dependent variable (CF_t) in the model can lead to endogeneity bias, using ordinary least squares (OLS) estimators may result in biased results.[25] As a result, in this study, the research model was fitted using the Generalized Method of Moments (GMM) to address this issue.

Dechow *et al.*[1] put forth two fundamental assumptions for future cash flow forecasting models. The first assumption is that sales follow a random walk process.[1] The second assumption is that earnings and components of working capital accruals have a fixed proportion of sales. As a result, it has been suggested that the growth rate of sales can have a simultaneous effect on both the working capital accruals variables (independent variables) and future operating cash flow (dependent variable) in the model. Therefore, the model structure changes from linear to nonlinear.

For this purpose, the Model in Eq. (2) can be presented with a gray box structure:

$$\begin{aligned}\mathrm{CF}_{it+1} = {} & \beta_0 + \beta_{1it}\mathrm{CF}_{it} + \beta_{2it}\Delta\mathrm{Inv}_{it} + \beta_{3it}\Delta\mathrm{AP}_{it} + \beta_{4it}\Delta\mathrm{AR}_{it} + \beta_{5it}\mathrm{Other}_{it} \\ & + \lambda_1\mathrm{Dep}_{it} + \lambda_2\mathrm{Lev}_{it} + \lambda_3\mathrm{Buscycle}_{it} + \lambda_4\mathrm{CurVol}_t + \lambda_5\mathrm{Sanc}_t \\ & + \varepsilon_{it+1}. \end{aligned} \tag{3}$$

The model in Eq. (3) in the gray box structure is called a clear box. The simultaneous effect of the sales growth rate variable on working capital accruals in the clear box model is calculated using Pade approximant as follows:

$$\beta_{it} = F(r_{t-1}.r_t) = F(r_{it-1}) = \frac{c_0 + c_1 r_{it-1} + c_2 r_{it-1}^2}{1 + d_1 r_{t-1} + d_2 r_{it-1}^2}. \tag{4}$$

The model in Eq. (4) is called the black box. A gray box structure could be used to estimate the model by integrating clear and black box structures. In stage 2 of the proposed approach in Fig. 1, we used Pade approximant to estimate the parameters in the gray box method for the following reasons; first, fewer parameters are needed for its estimation, and second, the output of Pade approximant is in the form of a fractional and nonlinear function.

Since Pade has a specific function format, it is possible to analyze the behavior of this function — which is obtained for the coefficient of each variable — in terms of the likelihood of the parameters' behavior and how they affect each other.[26] In the Pade approximant, the coefficient of the impact of the sales growth rate variable on cash flows is a nonlinear function. By creating this structure, the simultaneous effect of sales growth rate on future cash flow and accruals components could be examined in greater detail. After selecting the gray box's structure and the Pade approximant's functional form, the problem of estimating its parameters is raised. Estimating the parameters of the gray box model can be considered an optimization and search problem. Today, meta-heuristic algorithms are recognized as powerful methods for solving optimization problems.[27] The model obtained from the gray box method proposed in the study was fitted using the gray wolf meta-heuristic algorithm.[5]

3.2. *Grey wolf optimizer*

Grey wolf optimizer (GWO) is an efficient optimizer stimulated by the hunting mechanism of wolves. The increasing trend of applying GWO shows that although it is a simple algorithm with few control parameters, it effectively solves optimization problems.[28] The GWO is inspired by the hunting strategies and social hierarchy of grey wolves in nature.[5] They mostly prefer to live in an organized pack of 5–12 individuals, while in each pack, they have a dominant social hierarchy as alpha (α), beta (β), delta (δ), and omega (ω) types of grey wolves. The α wolves residing at the top of the hierarchy are the leaders of the pack. They are responsible for making decisions about hunting, moving, maintaining discipline, sleeping, and time to wake. The decisions of α are dictated to the pack, although some kind of democratic behavior has also been observed. β wolves are the second level of the hierarchy. They are subordinate to the α. The β helps α in making decisions and plays the role of advisor to the α. The wolves that occupy the fourth stage of the hierarchy (lowest level) are called the ω type of wolves. The ω plays the role of scapegoat and is responsible for maintaining the safety and integrity of the wolf pack. On the condition that a wolf does not belong to either a, β, or ω, then he/she is named δ. The δ follows α and β but they dominate the ω.[29]

The optimization process of the GWO algorithm is as follows. First, a group of grey wolves is randomly generated within a search space. During the course of iterations, α, β and δ guestimate the location of prey, and other wolves update their positions based on the location of α, β, and δ. Subsequently, the prey is encircled and the hunt is finished by attacking the prey when it stops moving. The GWO algorithm is shown in Algorithm 1.

An individual in GWO is constructed from a series of genes, as shown in Fig. 2. In this Figure, we codded the functional form of the proposed model in Eq. (3) and its parameters to a gray wolf. The variables in this function include c_0, c_1, c_2, d_1,

Algorithm 1. Pseudo-code of GWO.

Input: $\begin{cases} (n) & \text{Number of gray wolves in the pack} \\ (N_{\text{Iter}}) & \text{Number of iterations for optimization} \end{cases}$

Output: $\begin{cases} (X_\alpha) & \text{Optimal gray wolf position (the best parameters of Eq. (3))} \\ f(X_\alpha) & \text{Best fitness value} \end{cases}$

Initialize a population of n grey wolves positions randomly.
Find the α, β, and δ solutions based on their fitness values.
    While Stopping criteria not met **Do**
        For each Wolf$_i \in$ pack do
        Update current wolf's position according to Eq. (17)
        End
          I. Update a, A, and C.
          II. Evaluate the positions of individual wolves.
          III. Update α, β, and δ
    End

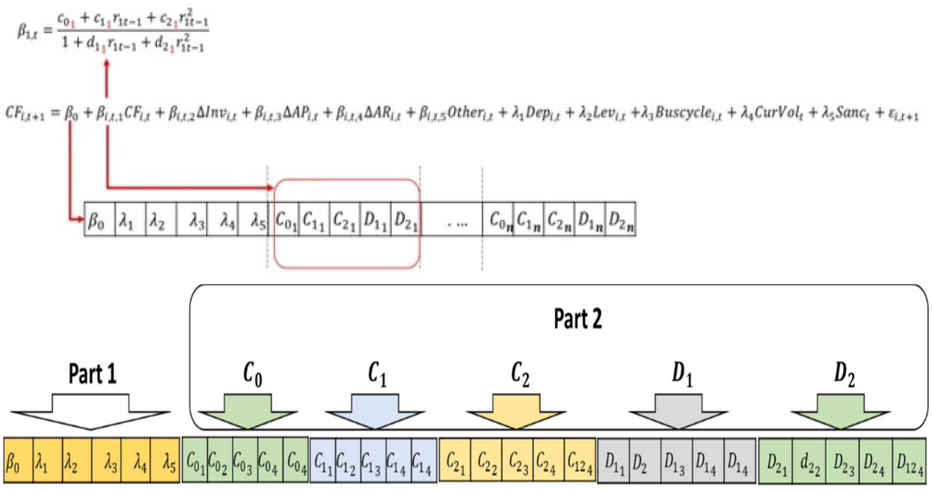

Fig. 2. Coding process of the problem of estimating the regression parameters of Pade function using the gray wolf algorithm.

and d_2. In addition, variable β_0 in the model must also be initialized. It is worth noting that each of the defined variables is initialized in five parts.

As can be seen, the individual in GWO consists of two parts. In the first part, the main parameters of the model in Eq. (3) are initialized as a matrix (Part 1). In the second part, Pade parameters are initialized (Part 2). The fitness function is achieved by applying an appropriate conversion to the objective function, i.e., the function to be optimized. This function evaluates each individual on the gray wolf algorithm with a numeric value that reflects its quality. The higher the quality of the individual, the higher the fitness of the individual, and the greater the likelihood of participation in the construction of the next generation. Since this study aims to diminish the forecast error of future cash flow, the mean absolute percentage error (MAPE) has been used as the fitness function.

In order to calculate the forecasting error in this research, four criteria, 1 — MAPE, 2 — Theil's U, 3 — Mean Absolute Error (MAE), and 4 — Root Mean Square Error (RMSE) are used as follows:

$$\mathrm{APE}_i = 100 \times \frac{|\mathrm{CF}_i - \mathrm{CF\ forecated}_i|}{\mathrm{CF}_i}, \tag{5}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum \mathrm{APE}_i, \tag{6}$$

Theil's

$$U = \frac{\sqrt{\left[\frac{1}{n}\sum_{i=1}^{n}(\mathrm{CF}_i - \mathrm{CF\ forecated}_i)^2\right]}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\mathrm{CF}_i)^2} + \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\mathrm{CF\ forecasted}_i)^2}}, \tag{7}$$

$$\mathrm{MAE} = \frac{1}{n}\sum \left|\frac{\mathrm{CF}_i - \mathrm{CF\ forecasted}_i}{\mathrm{CF}_i}\right|, \tag{8}$$

$$\mathrm{RSME} = \sqrt{\frac{1}{n}\sum (\mathrm{CF}_i - \mathrm{CF\ forecasted}_i)^2 + +}, \tag{9}$$

where CF_i is the actual cash flow of firm i, CF $\mathrm{forecasted}_i$ is the forecasted cash flow of firm i, and n is the number of sample firms.

3.3. *Data and sample research*

To conduct this research, we use a sample comprising all companies listed on the Tehran Stock Exchange for which the necessary data are available over a 14-year period from 2005 to 2019. As noted by Ref. 30, investment companies, financial institutions, and banks were excluded from the sample due to differences in the nature of working capital. Industries and firms that lacked sufficient data to estimate research models, as well as duplicate and inconsistent observations, were excluded from the sample. At the industry level, a minimum of 30 observations for each variable was required during the research period. At the firm level, a minimum of 10 non-missing observations for each variable was required. Based on these criteria, the final sample comprised 3,500 firm-year observations from 250 companies in nine industries. All variables were measured in the currency unit of Iran, the Rial. While dividing all continuous research variables by the period's average total assets helps address the issue of heteroscedasticity, all continuous variables were also winsorized at the 1% level to mitigate any potential data errors and scaling problems.

4. Research Findings

4.1. *Descriptive statistics of research variables*

Descriptive statistics analysis enhances the insight into the nature of the model's variables. In this regard, the skewness of variables CF, ΔAR, and ΔINV is 0.437, 0.443, and 0.257, respectively, all of which are smaller than 0.5. This indicates that these variables have a relatively symmetrical distribution. Besides, the low difference between the mean and median of the CF variable also indicates a symmetrical distribution.

4.2. *Results of the proposed model fitting using GMM*

Table 2 presents the results of estimating the research model using GMM. The results include the Sargan statistic for testing the validity of the instrumental variables, the Wald statistic for testing the overall significance of explanatory variables, and tests for autoregressive errors. The model estimation was based on data from 2006 to 2018 (training data). Then, using the coefficients obtained from the estimation, cash flow was forecasted for 2019 and compared with the actual cash flow of the same year (test data) to calculate the forecast error.

The Sargan statistic shows that the validity of the instrumental variables is not rejected. The Wald statistic confirms that a set of independent variables are collectively significant for the model. The AR(1) test shows that random error is serially correlated.

4.3. *The results of the proposed gray wolf algorithm*

This section uses a gray wolf algorithm to estimate the parameters of the model in Eq. (3) to develop the GWOGB model. In order to run the model, data derived from the 2006–2018 period is considered training data, and data from 2019 is the experimental data. A significant issue in executing a meta-heuristic algorithm is

Table 2. Descriptive statistics of research variables.

Variable	Mean	Median	Min	Max	SD	Skewness	Kurtosis
CF	0.115	0.101	−0.167	0.461	0.135	0.437	3.190
ΔAR	0.033	0.017	−0.319	0.421	0.112	0.443	5.436
ΔINV	0.024	0.015	−0.200	0.269	0.087	0.257	4.246
ΔAP	0.021	0.004	−0.279	0.429	0.095	1.09	7.988
Other	−0.074	−0.053	−0.693	0.436	0.230	−0.369	3.518
Lev	0.696	0.659	0.168	2.703	0.354	2.806	15.14
Dep	0.269	0.222	0	1.479	0.200	1.197	4.663
R	0.163	0.119	−0.677	1.547	0.398	1.013	5.422
Cycle	0.517	1	0	1	0.499	−0.068	1.004
Cur	1.158	0.059	0.853	1.869	0.292	1.611	4.117
Sanc	0.333	0	0	1	0.471	0.707	1.500

determining its parameters. In this regard, this research follows a trial-and-error approach. To do so, a set of values is randomly selected in the acceptable range of the parameters above, and the algorithm is performed using these parameters. Finally, the set of parameters with the least fitting error is selected. In this study, the number of candidate individuals in each iteration of the gray wolf algorithm is set to 50 and the number of iterations of the algorithm 80 was estimated.

4.4. *Comparison of the performance of fitting methods*

Table 3 shows the operating cash flow forecast error calculated based on two GMM and GWOGB methods.

Comparing the error calculation by these two methods reflects a significant drop in future cash flow forecast error in the gray wolf method. Therefore, estimating the research model using the gray box method and the gray wolf algorithm can provide a much more accurate forecast of future cash flow.

The t-test was utilized to test the significance of the difference in model forecast performance between GWOGB and GMM methods. For this purpose, the absolute

Table 3. Results of research model fitting using GMM.

Variable	Coefficient	Z-statistics
C	0.1212	2.47
CF	0.2118	19.52
ΔINV	0.1474	12.63
ΔAR	0.0461	4.95
ΔAP	0.1211	9.10
Other	0.0057	0.77
Dep	0.0878	12.47
R	0.0094	3.95
Lev	0.0506	12.18
Cycle	−0.0266	−14.65
Currency	0.0452	20.89
Sanction	−0.0371	−31.42
F-Statistics	7.62**	
Wald (joint) test (Chi^2)	608.1**	
Test for AR(1) errors (z)	−9.76**	
Test for AR(2) errors (z)	0.25	
Sargan over-identification test (Chi^2)	24.84	
Number of observations	3500	

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Table 4. Comparison of cash forecast error using GMM and GWOGB methods.

Fitting method	MAE	RMSE	Theil's U error index
GMM	0.102	0.1674	0.628
GWOGB	0.068	0.0901	0.196

Table 5. Comparison of predictive performance of research model based on GMM and GWOGB.

Estimation method	t-test statistics	p-value	Conclusion
GMM GWOGB	7.76	0.000	$\mu_{\mathrm{GWO}} < \mu_{\mathrm{GMM}}$

Please provide the citation for Table 5.

percentage error (APE) of the test data forecast was used in the t-test. According to Table 4, there is a significant difference between the performance of the fitted model with the GWOGB method and the fitted model with the GMM method, which suggests the high generalization power of the GWOGB method.

4.5. *Identify the source of operating cash flow forecast error by sensitivity analysis method*

Sensitivity analysis examines the impact of output variables on the input variables of a model. As stated earlier, in the Pade approximant, the coefficient of the impact of the sales growth rate variable on cash flows is a nonlinear function. The reason is that in the Pade structure, the coefficients of working capital accruals in the model are a function of the sales growth rate. By creating this structure, the simultaneous effect of sales growth rate on future cash flow and components of working capital accruals was investigated using the Pade function. Results of fitting the research model by the gray wolf method show the nonlinear effect of working capital accruals on future cash flow. In this section, by using sensitivity analysis, a comparison has been drawn between the nonlinearity of these coefficients in the gray wolf method and their linearity in the GMM method. In all the following figures, the linear graph indicates the coefficient calculated in the GMM method, and the curve diagram shows the shape of the coefficient obtained from the GWOGB method.

Figure 3 shows the coefficient of the CF variable (β_1) in the future cash flow forecasting model. The curved area in the figure above suggests that the effect of the CF variable alters at different levels of sales growth rates. With an increase in sales growth rate, the CF variable rises, and its impact on future cash flow increases. This indicates the nonlinear effect of the CF variable on future cash flow, which is due to changes in the sales growth rate. In fitting the research model using the regression method, the coefficient of the CF variable was estimated at 0.2118. Therefore, in fitting the model using the regression method, the nonlinear effect of this variable on future cash is not considered.

According to Fig. 4, in the GWOGB method, the effect of ΔINV on future cash flow is more significant for a negative sales growth rate, reaching its peak at zero sales growth. At the positive sales growth rates, however, its effect attenuates. This means that an elevated sales growth rate mitigates the effectiveness of inventory changes in the cash flow forecasting process. In fitting the model by the GMM method, this variable's coefficient was considered constant (0.1474).

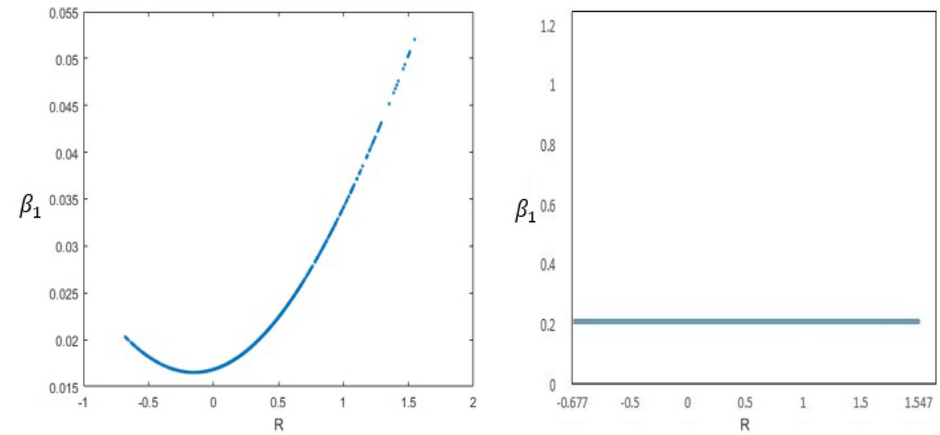

Fig. 3. Comparing the coefficient change of variable CF at different levels of sales growth rate in GMM and GWOGB methods.

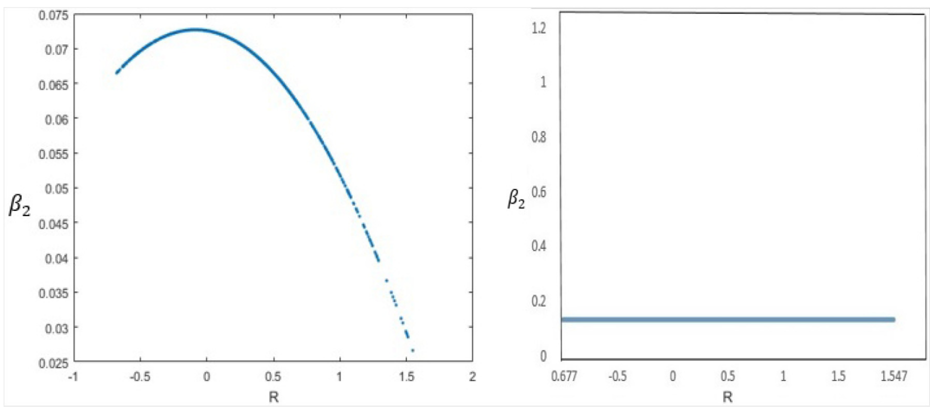

Fig. 4. Comparing coefficient change of ΔINV at different levels of sales growth rate in GMM and GWOGB methods.

The coefficient β_3 in the forecast model indicates the effect of the ΔAP on future cash flow. Fitting the prediction model using GWOGB shows the nonlinear effect of this variable on future cash flow. Before the sales growth rate reaches the range of 0.5, this coefficient follows an increasing trend, with its effect peaking at the sales growth rate of 0.5. However, from this point onwards, a downward trend emerges so that the effect of change in receivables on the prediction of future cash flow diminishes. In the regression fit of the research model, the coefficient of ΔAP at all sales growth rates was estimated to be 0.1211.

Figure 6 shows the coefficient change of ΔAR at different sales growth rates. This coefficient falls with an increase in the sales growth rate. At higher sales growth

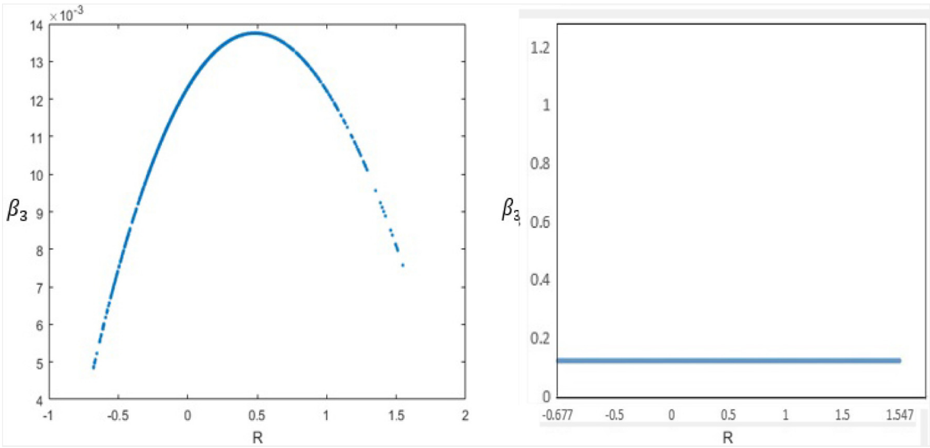

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Fig. 5. Comparing the coefficient change of ΔAP variable at different levels of sales growth rate in GMM and GWOGB methods.

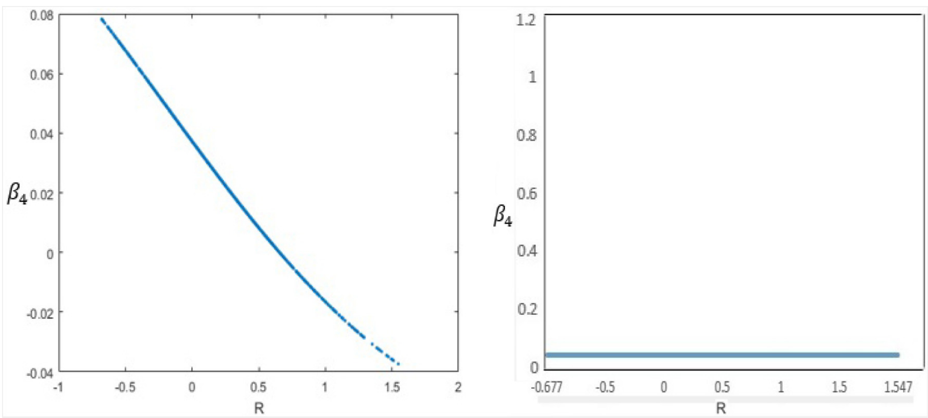

Fig. 6. Comparing the coefficient change of ΔAR variation at different sales growth rate in GMM and GWOGB methods.

rates, the effect of changes in receivables on future cash flow forecasts tapers off. The coefficient of changes in receivables on the regression fit of the model is considered to be constant (0.041).

The coefficient of other working capital accruals in the future cash flow forecasting model also displays a nonlinear pattern in fitting the model using the gray wolf method. With an increase in sales growth rate, the impact of these items on future cash flow in the forecast model improves. The effect of these items is the opposite of changes in receivables. In estimating the cash flow forecasting model by the regression method, the variable coefficient of other working capital accruals was estimated to be 0.0057.

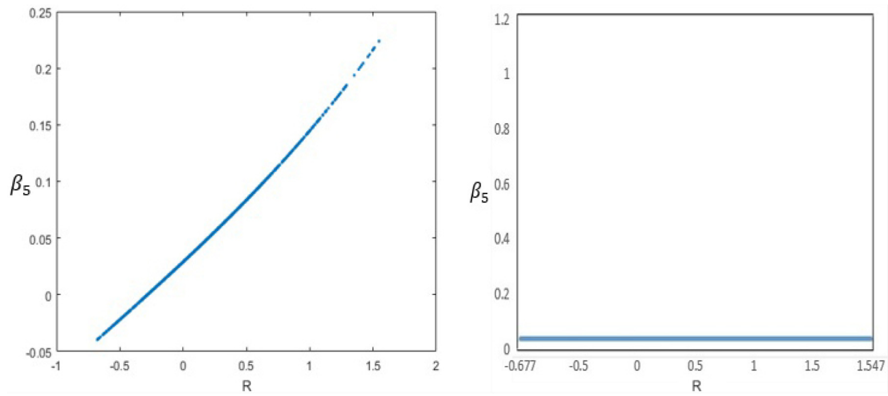

Fig. 7. Comparing change of coefficient in other working capital accruals at different sales growth rates in GMM and GWOGB methods.

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5. Discussion

The primary objective of this research is to develop a comprehensive model for predicting future cash flows by controlling the nonlinear effect of sales growth rate on accruals and other relevant variables. The study aims to address potential biases in cash flow forecasting models by using advanced statistical techniques to control for nonlinear effects and identify the most relevant variables affecting cash flow forecasting accuracy.

The proposed cash flow forecasting model in the study offers several managerial insights that can be useful for financial analysts and decision-makers. The study highlights the importance of incorporating new variables and modifying the model structure to improve forecast accuracy. Incorporating market and economy-based variables, such as exchange rate fluctuations and economic sanctions, can provide a more comprehensive understanding of a company's financial performance and future cash flow potential.

The study also emphasizes the use of the Gray Box method and the Gray Wolf algorithm for estimating the parameters of the model and optimizing the forecast accuracy. This approach can enable financial analysts and decision-makers to make more informed decisions based on accurate cash flow forecasts, which, in turn, can enhance a company's financial performance and stock value.

Furthermore, the study highlights that addressing firm heterogeneity in cross-sectional research designs is crucial for accurate cash flow forecasting. This means that financial analysts should consider the unique characteristics and operating structures of individual companies when developing cash flow forecasting models.

Overall, the study provides valuable insights for financial analysts and decision-makers to improve the accuracy of cash flow forecasting and make informed decisions based on reliable financial information. By incorporating new variables, modifying the model structure, and addressing firm heterogeneity, financial analysts can develop more accurate cash flow forecasting models, leading to improved financial performance and decision-making.

6. Conclusion

The findings of this study have significant implications for financial analysis and decision-making. The study suggests that accrual-based earnings measures provide a better basis for predicting future cash flows, which is consistent with previous studies and practitioner literature. The breakdown of accruals into additional components, such as working capital accruals, has provided a more accurate forecast of operating cash flow. The study highlights the importance of incorporating new variables, such as market and economy-based variables, to improve the accuracy of cash flow forecasting. The results also suggest that the gray box method and the gray wolf algorithm (GWOGB) are effective in reducing future cash flow forecast errors compared to the GMM.

Findings are aligned with previous research that has highlighted the limitations of linear models, such as multivariate linear regression models, in cash flow forecasting. The study's proposed GWOGB model incorporates a black box function to calculate the simultaneous effect of the sales growth rate variable on working capital accruals, addressing one limitation of previous models. The GWOGB model also incorporates market and economy-based variables, addressing another limitation of previous models.

The sensitivity analysis indicates the importance of considering the nonlinearity of coefficients in cash flow forecasting models. The nonlinear effect of working capital accruals on future cash flow in the gray wolf method emphasizes the importance of using nonlinear models, such as the gray box method, in cash flow forecasting. The study's findings suggest that sensitivity analysis can be used to identify the source of forecast errors in operational cash flow.

Findings have significant implications for financial analysis and decision-making. Accurate cash flow forecasting is crucial for evaluating a company's financial health and assessing its capacity to produce cash in the future. The study's proposed GWOGB model and sensitivity analysis methodology can be used by financial analysts and decision-makers to improve cash flow forecasting accuracy. The study's findings also highlight the importance of considering the nonlinearity of coefficients in cash flow forecasting models. In practice, companies can use the GWOGB model to improve their cash flow forecasting accuracy.

The limitations of this research include its reliance on a single lag for predicting future operating cash flows for the independent variables, which limits its prediction horizon to the short-term. Additionally, the study only relied on historical information from companies listed on the Tehran Stock Exchange, and the lack of access to similar financial markets prevented the comparison of results. To overcome these limitations, future research should consider incorporating the following aspects: First, large-scale financial data from multiple countries should be utilized to enable more extensive analysis. This would allow for a broader range of variables and longer prediction horizons to be considered, improving the model's accuracy and flexibility. Second, new data mining methods can be adopted to improve the model's efficiency and enhance the credibility of the findings. Overall, addressing these limitations will help us improve the model's reliability and applicability to a wider range of financial markets and contexts.

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