Turkish Journal of Forecasting vol. 8 no. 2 (2024) pp 16-25

Content list available at JournalPark

Turkish Journal of Forecasting

Journal Homepage: tjforecasting.com

Development of Comparative Forecasting Models of Daily Prices of Aggressive Pension Mutual Funds by Univariate Time Series Methods

Simge Eşsiz[1], Muhammed Ordu[1,*]

[1]*Department of Industrial Engineering, Faculty of Engineering and Natural Sciences, Osmaniye Korkut Ata University, Karacaoglan Campus, 80010 Osmaniye, Turkey*

Abstract

The primary goal of the individual pension system is to enhance retirees' living standards by generating supplementary income through the investment of their savings during retirement. This involves guiding individuals to invest their savings in pension mutual funds. Additional forecasting studies are necessary to provide guidance for both participants and companies regarding the future trajectory of these funds. There is a notable dearth of research in the literature concerning the forecasting of individual pension mutual funds. This study intends to fill this gap by concentrating on the comparative forecasting modelling for aggressive pension mutual funds. Therefore, this research develops comparative forecasting models using Autoregressive Integrated Moving Average and Exponential Smoothing techniques for the daily prices of pension mutual funds categorized as aggressive risk and compares with Naïve Method. The study utilizes data from 2020 to 2023 pertaining to a pension mutual fund provided by a Turkish pension company. The dataset is split into a training set (75%) and a test set (25%). Mean Absolute Percentage Error is employed to gauge the error measurement values of the training and test sets of the developed forecasting models. The findings reveal that despite exhibiting poorer performance in the training sets for all funds, the Naive method demonstrated superior performance compared to the ARIMA and exponential smoothing methods in the test set. In the test set as second optimal forecasting model, Autoregressive Integrated Moving Average model performs best for the İş Bank participation index funds, whereas Exponential Smoothing forecasting models yield the lowest Mean Absolute Percentage Error values for equity, group equity, and secondary equity funds. This research can serve as a decision-making tool for the effective management of high-yield pension mutual funds and aid pension companies in enhancing the appeal of their product offerings to customers.

Keywords: Aggressive Pension Mutual Fund, Individual Pension System, Forecasting, Time Series Analysis.

1. Introduction

The Individual Pension System (IPS) has become an increasingly important investment system in recent years. IPS allows individuals to redirect their savings into investments to obtain additional income during retirement. The system aims to improve living standards during retirement (Mutlu et al, 2016). The types of funds offered by IPS vary in risk and return levels according to participants' preferences. These fund types generally include equity funds, bond and fixed-income funds, mixed funds, money market funds, and variable funds. These fund types can be chosen by participants based on their risk tolerance and retirement goals. Additionally, funds differ in terms of risk and return rates. In this context, individual pension companies typically offer funds with varying risk and return levels such as money market, equity, precious metals, debt instruments, participation, mixed, index, fund basket, variable, and standard funds to their customers (Pension Monitoring Center, 2024).

[*] Corresponding Author.
E-mail addresses: simgeessiz01@gmail.com (Simge Eşsiz), muhammedordu@osmaniye.edu.tr (Muhammed Ordu)

ORCID ID:
Simge Eşsiz: 0009-0007-1717-7063
Muhammed Ordu: 0000-0003-4764-9379

Forecasting the return rates of financial investment instruments holds critical importance for both investors and financial institutions for various reasons. When making investments, investors evaluate potential future returns to make decisions. Forecasting return rates helps investors assess the balance between risk and return. The relationship between expected return and risk enables investors to diversify their portfolios appropriately and minimize risk. Forecasting is crucial for individual pension mutual funds as it aids in formulating strategies necessary to ensure individuals have sufficient savings during retirement. Forecasting is necessary to determine how much savings individuals need to meet their financial needs during retirement. Accurate forecasts assist individuals in evaluating their risk-return balance effectively (Ordu, 2022).

Time series methods are statistical and mathematical techniques used to analyse, model, and predict future values of observed data over time. Time series methods generally include simple average, moving average, exponential smoothing, autoregressive integrated moving average (ARIMA), and seasonal autoregressive integrated moving average (SARIMA) methods. Univariate time series methods are used to model the behaviour of only one variable over time. These methods analyse relationships and patterns between past data points and attempt to predict future values based on this information. Forecasting future values guides decision-makers in strategic planning and policy formulation processes. Univariate time series analysis is also important for risk management. Forecasting future values can be used to identify potential risks and take measures against these risks (Makridakis et al, 1998).

This research aims to develop comparative forecasting models for pension mutual funds with high-risk and high-return characteristics. The study utilizes ARIMA and Exponential Smoothing methods, both of which are univariate time series analysis and aims to compare with Naïve method. Data spanning from 2020 to 2023 from a pension mutual fund offered by a Turkish pension company is employed. Specifically, the data pertains to four funds categorized as having aggressive risk profiles: Equity Fund, Group Equity Fund, Secondary Equity Fund, and İş Bank Participation Index Fund. The dataset is split into a training set (75%) and a test set (25%). Mean Absolute Percentage Error (MAPE) serves as the metric for assessing error in both the training and test sets of the developed ARIMA, exponential smoothing and Naïve models. The performance of forecasting models for each pension mutual fund is compared based on their MAPE values. We contributed to the knowledge as follows: 1) Developing a comparative forecasting approach to gain deeper insights into the future trends of pension mutual funds in Turkey, 2) Being pioneer the application of more popular and hybrid forecasting approaches within this domain, utilizing univariate time series data of pension mutual funds, and 3) Providing a forward-looking perspective for the Turkish individual pension system and its various stakeholders.

Consequently, there is a pressing need for an accurate and dependable framework for modelling the daily price forecasts of long-term pension mutual funds. This framework is essential to assess and address the requirements for more profitable investments by participants and other stakeholders, both now and in the future. By doing so, this study will empower relevant pension companies to develop superior and more lucrative funds, while also optimizing the allocation of investment instruments within the fund's structure. Additionally, it will serve as a guide for participants, aiding them in maximizing profits upon reaching investment maturity and assisting them in making informed decisions regarding which funds to invest in during their investment period.

2. Literature Review

Several studies have addressed fund and risk management within the context of the individual pension system. For instance, Ural and Adakale (2009) utilized value at risk analysis to assess the individual pension system in Turkey in terms of risk. Meanwhile, Eken and Gaygısız (2010) sought to identify risks and assess the level of implementation in Turkey by considering exemplary practices from international institutions regarding risk management in individual pension companies. Sarsıcı et al (2017) investigated wealth funds, which are becoming increasingly significant in global financial markets.

The performance of individual pension funds and companies has been extensively analysed using various multi-criteria decision-making approaches. For instance, Korkmaz and Uygurtürk (2007) measured the performance of 46 Turkish pension funds between January 2004 and June 2006. Alptekin and Şıklar (2009) assessed the performance of pension mutual funds in Turkey using the Technique for Order Preference by Similarity to Ideal (TOPSIS) method, a multi-criteria decision-making approach. Ertuğrul and Öztaş (2016) employed Complex Proportional Assessment (COPRAS) and TOPSIS methods to select individual pension plans, aiming to identify the most suitable retirement plan for potential participants in the individual pension system. Ege et al (2016) analysed the performance of 11 income borrowing standard pension funds from January 2012 to December 2014. Şahin and Başarır (2019) focused on evaluating the financial performance of individual pension companies in Turkey. Aydin (2019) assessed the financial performance of companies in the life/pension insurance sector in Turkey, employing Criteria Importance Through Intercriteria Correlation (CRITIC) and TOPSIS methods to evaluate companies' performance from 2015 to 2017. Acer et al (2020) aimed to evaluate the performance of individual pension companies in Turkey using multi-criteria decision-making methods (i.e., Entropy and COPRAS) based on data from 17 IPS companies. Demir et al (2020) examined the performance of 18 individual pension companies under the supervision and control of the Pension Monitoring Center. Çınaroğlu (2022) discussed the utilization of entropy-based Evaluation based on Distance from Average Solution (EDAS) and Combinative Distance-Based Assessment (CODAS) methods to evaluate the performance of individual pension companies. Ayaydın (2013) and İlhan (2021) examined the performance of pension mutual funds in Turkey. Arslan and Çelik (2018) conducted a study comparing the performance of pension mutual funds in Turkey with the performance of the BIST-100 index.

Simulation and optimization methods are widely utilized across various fields (Kirli Akin and Ordu, 2022). These techniques are also employed to analyse and enhance the effectiveness of the individual pension system, providing valuable insights for policymakers and stakeholders in the field although studies in this area are relatively rare. For example, Korkmaz and Uygurtürk (2015) addressed the challenges faced by social security systems globally and the issues within Turkey's public social security system. They emphasized the significance of structural reforms and the individual pension system in addressing these challenges. The study outlined the processes involved in constructing optimal portfolios using the modern portfolio theory developed by Harry Markowitz. Mutlu et al (2016) conducted a study comparing returns between the individual pension system and the bank's deposit system. They evaluated four different scenarios using net present value and profitability index methods. Financial forecasts were developed using artificial neural networks and Monte Carlo simulation methods. Ordu (2022) introduced a simulation-based decision-making approach in his study, examining the feasibility of the Turkish individual pension system for participants under various scenarios. Additionally, Ordu (2023) utilized the system dynamics simulation method to analyse pension mutual funds in the attack fund category from the perspective of participants.

Forecasting methods have been widely applied across various fields (Ordu et al, 2023), including the development of forecasting models for financial investment instruments, such as products within the individual pension system. For instance, Onocak and Koç (2018) conducted a study using the artificial neural networks (ANN) method to predict pension investment fund stock prices. Bayrakçı and Aksoy (2019) aimed to estimate the number of participants in the individual pension system in Turkey and the amounts directed to investment for the upcoming period. They provided insights into the predictions made using the Gray Forecast G(1,1) model. Kayakuş and Terzioğlu (2022) focused on estimating the net asset values of 12 individual pension funds operating in Turkey. They utilized multilayer perceptron (MCP) and multiple linear regression methods to estimate the net asset values of these funds. In addition, numerous research in the literature have indicated a tendency to favour classical forecasting methods for estimating financial instruments. For example, Bollapragada et al (2013) examined the suitability of the Exchange Traded Fund for investment and suggests using multiple regression for forecasting the price of the fund, achieving promising results with low forecast errors across several metrics. Khashei et al (2017) proposed an enhanced version of hybrid neural-based models by integrating autoregressive integrated moving average (ARIMA) and artificial neural networks (ANNs) for forecasting financial time series. Ozturk et al (2017) focussed on usage of Bayesian Regression Model to forecast BIST 100 Index and taken into consideration macroeconomic factors that impact the stock index, including interest rates, exchange rates, money supply, inflation, gold, and oil prices. Sindelar (2019) explored that both ARIMA and simple moving average methods than the common quantitative methods are found to be notably less accurate. Shen (2022) focused on forecasting the closing price of the Shanghai Stock Exchange Fund Index using the ARIMA and Error-Trend-Seasonal (ETS) models. The forecasting performance of the ARIMA model as compared with SES, DES, and TES models, the DES model exhibits the highest accuracy in predicting short-term changes in the fund market. Fan (2022) used ARIMA model to forecast Monetary Fund. Louisa (2022) applied ARIMA models to forecast the volume of internet users applying for retirement insurance online. This prediction is based on monthly data obtained from the Social Security Administration spanning from January 2008 to October 2020.

3. Materials and Method

3.1. Data

The data used in this study belongs to the pension mutual funds of a Turkish pension company. The data we used consists of four funds belonging to the aggressive risk category. These are Equity Fund, Group Equity Fund, Second Stock Fund, and İş Bankası Participation Index Fund. Equity Fund, Group Equity Fund, and Second Stock Fund allocate at least 80% of their portfolio to stocks actively traded on the Borsa Istanbul. These funds aim to capitalize on fluctuations in the domestic stock market to the fullest extent possible. Their portfolios target capital gains by trading shares of companies with high liquidity, substantial market value, and promising future potential. As for the İş Bank Participation Index Fund, a minimum of 80% of its total value remains consistently invested in stocks of companies listed in the Türkiye İş Bank Participation Index. The data has been obtained from the pension fund trading platform (BEFAS, 2024) and covers the period between 2020 and 2023. The data is divided into training set (%75) and test set (%25).

3.2. Autoregressive Integrated Moving Average (ARIMA) Method

The autoregressive (AR) process forecasts future values of a variable based on its past values, as depicted in Equation (1). Conversely, the moving averages (MA) process predicts forthcoming values by considering past errors, outlined in Equation (2) (Kuzu, 2022).

$$Y_t = \delta + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \phi_3 Y_{t-3} + \cdots + \phi_p Y_{t-p} + e_t \tag{1}$$
$$Y_t = \delta + e_t + \phi_1 e_{t-1} + \phi_2 e_{t-2} + \phi_3 e_{t-3} + \cdots + \phi_q e_{t-q} \tag{2}$$

where δ is constant, Y_t represents the observation of term t, ϕ_i means model parameters, p is the degree of the model and e_t is the error term (Kuzu, 2022).

ARMA (Autoregressive Moving Average) models integrate autoregressive (AR) and moving average (MA) components, proving to be efficient tools for analysing diverse time series. The AR component models the relationships among previous values, while the MA component captures random noise and rectifies irregular patterns. By eschewing high-order AR or MA models, ARMA models require fewer parameters, enhancing simplicity and generalizability. Moreover, they suit stationary stochastic processes, wherein statistical properties remain constant over time. ARMA models find utility in analysing statistical properties, discerning trends, forecasting future values, and identifying patterns. Model selection hinges on dataset characteristics and analytical objectives. The equation representing the ARMA model is provided in Equation (3). Expressed in Equation (4), the stationarity condition of the ARMA model underscores the stability of statistical properties over time (Kuzu, 2022).

$$Y_t = \delta + \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} + e_t + \theta_1 e_{t-1} + \cdots + \theta_q e_{t-q} \tag{3}$$
$$\phi_1 + \phi_2 + \phi_3 + \cdots + \phi_p < 1 \tag{4}$$

Box-Jenkins models, known as ARIMA, are prevalent statistical tools for time series analysis. These models amalgamate AR, MA, and ARMA components, employing unit root tests to ensure series stationarity and capturing trend, seasonality, and error components. ARIMA notation, expressed as (p,d,q), entails "p" denoting the autoregressive term, "q" indicating the moving average term, and "d" representing the number of differencing operations (Kuzu, 2022).

The ARIMA technique generally involves three primary phases: 1) Identification, 2) Estimating and Testing, and 3) Utilization (Makridakis et al, 1998). In the first step, data preparation and model selection are key. Initially, non-stationary patterns in the time series lead to positive autocorrelations. Therefore, it's crucial to transform non-stationary data using differencing methods. Equation (5) outlines the process of taking the first difference, where Y_t represents the observation at time t, and Y_{t-1} represents the observation at time (t-1).

$$Y_t' = Y_t - Y_{t-1} \tag{5}$$

Next, the process of model selection allows for determining the appropriate values of AR (p) and MA (q) in an ARIMA model. In the second step, computer programs automatically calculate the optimal parameters for ARIMA models. This involves generating initial parameter values, and through an iterative process, the best model is identified. Least squares or maximum likelihood estimation methods are utilized to accurately determine the ARIMA model. In the last step, the selected and validated ARIMA model generates the estimated values (Makridakis et al, 1998).

3.3. Exponential Smoothing Method

Exponential smoothing (ES) stands out as one of the most commonly employed forecasting techniques. A notable characteristic is its utilization of exponentially decreasing weights as observations age (Makridakis et al, 1998). A total of 15 types of ES models that do not incorporate error terms is illustrated in Table 1. However, when considering both additive and multiplicative errors, a total of 30 ES models emerge. Among these, the (N,N) model represents single exponential smoothing (SES), the (A,N) model signifies Holt's linear model, and the (A,A) model denotes Holt-Winters' additive model. Additionally, the (A,M) model corresponds to Holt-Winters' multiplicative model, as highlighted by Hyndman et al (2008). A damped method is implemented to diminish the influence of the trend toward the conclusion of a time series within the period utilized for estimation. This approach, as noted by Hyndman et al (2008), is often effective in practice.

The Single Exponential Smoothing (SES) method, denoted as (N,N), incorporates the previous observation value and the previous forecast error multiplied by a constant α, which typically ranges between 0 and 1. Consequently, if the prior forecast underestimated the actual value, the subsequent forecast will be adjusted upward; conversely, if the previous forecast overestimated, the subsequent forecast will be adjusted downward. This mechanism enables the model to adapt to changing trends over time. Holt's Linear Method (A,N) extends beyond SES by incorporating a trend component. It introduces two adjustable parameters (α and β), each ranging between 0 and 1. The Damped Trend model (Ad, A) is an enhancement of Holt's linear model, where a damped trend is integrated to attenuate the influence of the trend towards the end of the time series period. The Holt-Winters Method facilitates forecasting when both trend and seasonal components are present. These components can be combined either additively or multiplicatively, offering flexibility in modelling various types of time series data (Hyndman et al, 2008).

Table 1. Types of ES methods (Hyndman et al, 2008)

Trend Components	Seasonal Components		
	N (None)	A (Additive)	M (Multiplicative)
N (None)	N, N	N, A	N, M
A (Additive)	A, N	A, A	A, M
A_d (Additive damped)	A_d, N	A_d, A	A_d, M
M (Multiplicative)	M, N	M, A	M, M
M_d (Multiplicative damped)	M_d, N	M_d, A	M_d, M

The exponential smoothing method generally involves five primary stages: 1) Partitioning the dataset into training and test sets, 2) Selecting an exponential smoothing technique, 3) Training the model, 4) Assessing the model's performance using the test set, and 5) Generating forecasts (Makridakis et al, 1998). In the first step, the data is divided into two sets: Training set and testing set. In the second step, one method is selected from a pool of 30 different types of exponential smoothing methods, as elaborated earlier. After that, to construct a forecasting model, a training set is utilized. In this study, the ets() function in R, developed by Hyndman and Khandakar (2008), is employed to identify the optimal exponential smoothing (ES) models. This function automatically determines the best ES model for the data by assessing the Akaike Information Criterion (AIC) values (Hyndman and Khandakar, 2008). In the fourth step, once a model is constructed, the forecast accuracy for the validation set is evaluated using assessment criteria such as MAE (mean absolute error), MAPE (mean absolute percentage error), or MASE (mean absolute scaled error). And the final step, the selected and validated exponential smoothing (ES) model generates the estimated values.

4. Results and Discussion

The RStudio program was preferred for the solution of the prediction techniques method. RStudio utilizes the Akaike Information Criterion (AIC) to determine the best prediction model (Ordu and Zengin, 2020). Akaike's Information Criterion (AIC) serves to penalize the model's fit, typically measured by the sum of squared errors (SSE), by taking into account the number of parameters that required to be forecasted (Hyndman and Athanasopoulos, 2014). AIC, AICc and BIC (Bayesian Information Criterion) values for the ARIMA and Exponential Smoothing methods are provided in Table 2.

Table 2. Statistical values related to the ARIMA and Exponential Smoothing (ES) methods

Fund	AIC Values		AICc Values		BIC Values	
	ARIMA	ES	ARIMA	ES	ARIMA	ES
Equity Fund	-5925.40	-3560.68	-5925.38	-3560.60	-5916.15	-3537.55
Group Equity Fund	-6114.72	-3833.23	-6114.57	-3833.15	-6082.35	-3810.10
Second Stock Fund	-6893.88	-4600.96	-6893.73	-4600.88	-6861.51	-4577.82
İş Bank Participation Index Fund	-6788.93	-4636.23	-6788.85	-4636.15	-6765.81	-4613.10

4.1. Development of ARIMA Forecasting Models

The Autoregressive Integrated Moving Average (ARIMA) method determined the best fitting models for daily price predictions for four funds as follows: ARIMA(0,2,1) for Equity Fund, ARIMA(3,2,3) for Group Equity Fund, ARIMA(3,2,3) for Second Stock Fund, and ARIMA(2,2,2) for İş Bank Participation Index Fund, each with their respective parameter values. The ARIMA(0,2,1) model for the Equity Fund represents a time series model that lacks autoregressive (AR) terms and has been differenced twice (d=2). This model allows for the prediction of the second differences of the values at the current time point by associating them with moving averages of errors from previous time points. The MA(1) term indicates the association of the values at the current time point with the moving average of errors from previous time points, signifying that the model only considers the impact of past errors on predictions. The double differencing (d=2) may have been employed to ensure stationarity in the data series to address trends or seasonal variations. The ARIMA(0,2,1) model can be utilized to ensure stationarity in the time series and address the relationship between errors at current and previous time points. However, it is crucial to conduct goodness-of-fit tests when evaluating the performance of the model.

The ARIMA(3,2,3) model for the Group Equity Fund and the Second Stock Fund is a time series model incorporating autoregressive (AR) and moving average (MA) terms, with double differencing (d=2). This model predicts the second differences of current values by relating them to values at the previous three time points. AR terms signify the relationship between current and past values, while MA terms connect current values to moving averages of past errors. This model considers both past values and errors in predictions. Additionally, double differencing (d=2) ensures stationary data and eliminates trends or seasonal patterns. The ARIMA(3,2,3) model addresses trends, seasonality, and autocorrelation in complex time series data. However, selecting suitable parameters and accurately fitting the model are crucial due to its complexity.

The ARIMA(2,2,2) model for the İş Bank Participation Index Fund describes a time series model that integrates autoregressive (AR) and moving average (MA) components, with a double differencing approach (d=2). This model forecasts the second differences of current values by correlating them with AR and MA terms of values at the preceding two time points. The AR(2) component indicates the link between current values and those from two time points earlier. Meanwhile, the MA(2) component suggests that current values are associated with the moving averages of errors from the same previous time points. This model is valuable for ensuring time series stability and addressing relationships between current and past time points. However, proper parameter selection and accurate model fitting are crucial due to its complexity. Moreover, conducting fitness tests is essential when assessing the model's effectiveness. Figure 1 displays all graphs generated using the RStudio program for ARIMA models.

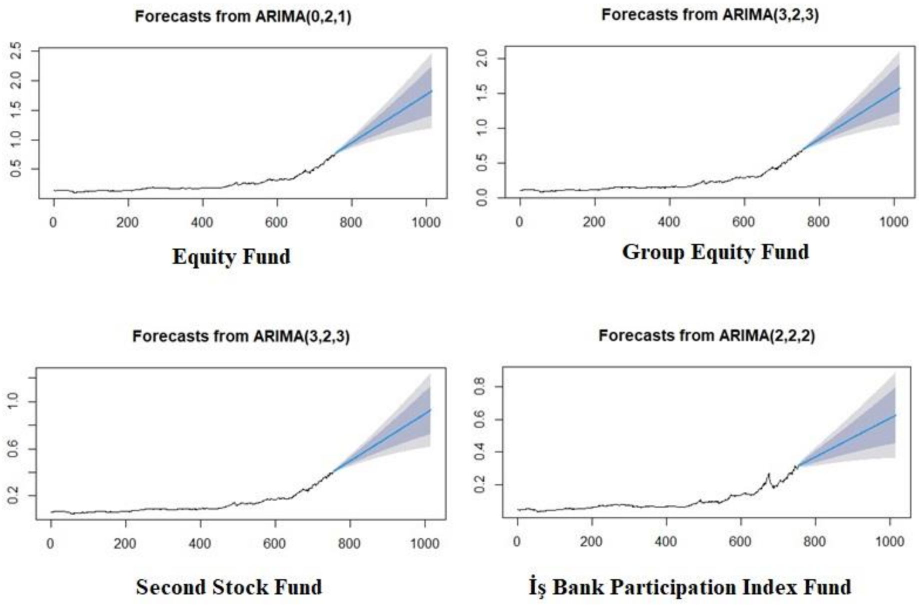

Figure 1. Forecast Graphs from ARIMA Models for Equity Fund with 80% and 95% confidence intervals

4.2. Development of Exponential Smoothing Forecasting Models

The ets() function in RStudio is a function used for time series analysis. It determines the most suitable ETS (Error-Trend-Seasonality) model for a given time series out of a total of 30 exponential smoothing methods available. This function calculates and presents the most appropriate one to users, considering the characteristics of the data and the specific features of the time series. This allows users to make more accurate forecasts on their time series data. The Exponential Smoothing method was employed for daily price predictions, for four funds as follows: ETS(M,A,N) for all funds. These parameter value represents the best fitting models for each respective fund. The ETS(M,A,N) model represents a time series model in the Error-Trend-Seasonality method. The "M" parameter specifies how the Trend component will be modelled. Additionally, the "A" parameter also determines how the Seasonality component will be modelled. The "A" option indicates that the Seasonality component exhibits a constant expansion or contraction in the data series, implying an additive component. The "N" parameter specifies how the Error component will be modelled. The "N" option indicates that the Error component follows a classical normal distribution. This implies that errors have a mean of zero and a constant variance. In summary, the ETS(M,A,N) model is used for situations where there is a constant increase or decrease representing the trend in the dataset and a seasonal pattern that exhibits a constant expansion or contraction. It assumes that errors follow a classical normal distribution. This model is commonly used to identify trend and seasonal patterns in the dataset. Figure 2 display the all graphs generated using the RStudio program.

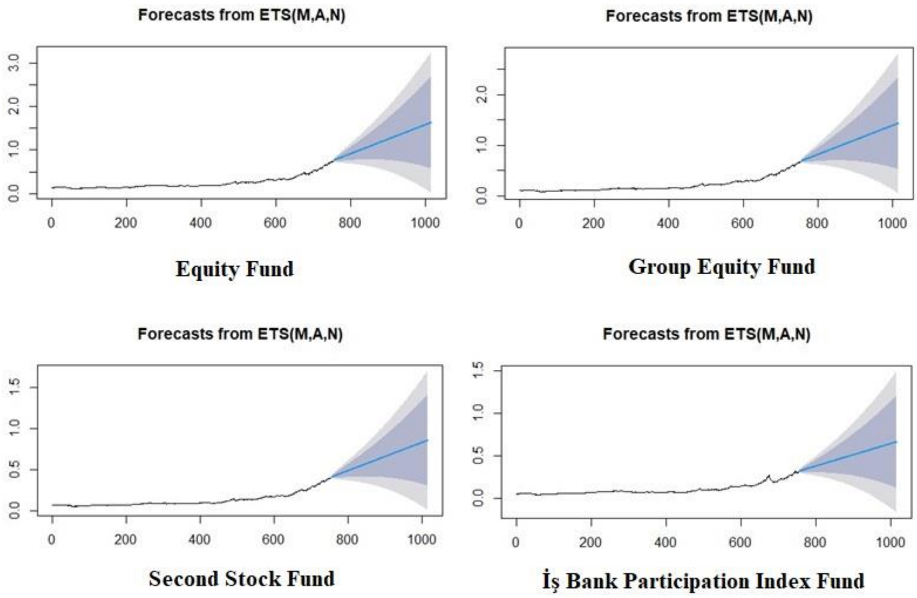

Figure 2. Forecast Graphs from ARIMA Models for Equity Fund with 80% and 95% confidence intervals

4.3. Comparison of Forecasting Models

Table 3 provides comparative MAPE values of the forecasting methods. Furthermore, the effectiveness of these methods has been also evaluated in comparison to the Naive method involving simply setting all forecasts to be equal to the value of the last observation (Hyndman and Athanasopoulos, 2014). While the Naive method didn't outperform in the training set for all funds, it exhibited notably lower MAPE values in the test set compared to the other two methods, demonstrating superior performance. On the other hand, although the forecasting models developed with the exponential smoothing method for the İş Bank Equity Index Fund pension mutual funds have been better trained, as understood from the test set, Naive method has produced more reliable forecast values. Additionally, Group Equity Fund and Second Stock Fund pension mutual funds have been better trained with the exponential smoothing method and have produced more accurate forecast values with Naive method. Finally, the forecasting model developed for the Equity Fund pension mutual fund has been better trained with the ARIMA method, while it has produced more robust and reliable forecast values with the Naive method.

Table 3. Comparison of Forecasting Methods based on MAPE

Funds	Forecasting Methods	Error Measurement Values (MAPE)	
		Training Set	Test Set
Equity Fund	Naïve Method	1.1395	**1.6141**
	ARIMA	**1.1019**	32.2052
	Exponential Smoothing	1.1056	24.5315
Group Equity Fund	Naïve Method	1.1367	**1.6011**
	ARIMA	1.1207	29.7598
	Exponential Smoothing	**1.1055**	23.8912
Second Stock Fund	Naïve Method	1.1358	**1.6021**
	ARIMA	1.1212	30.0369
	Exponential Smoothing	**1.1052**	24.8428
İş Bank Equity Index Fund	Naïve Method	1.3804	**1.9032**
	ARIMA	1.3736	28.3650
	Exponential Smoothing	**1.3651**	30.1614

5. Conclusions

The Individual Pension System (IPS) is an increasingly important investment system in recent years. IPS aims to increase individuals' standards of living during retirement by directing their savings towards investment and obtaining additional income during retirement. Participant and government contributions directed to the Individual Pension System are invested in pension mutual funds. The types of funds offered to participants vary depending on the risk and return situation. There are many types of funds. In this study, the development of comparative forecasting models for pension mutual funds in the aggressive risk category is aimed. The data used in this context belong to a Turkish pension company's pension mutual funds. The data used consist of four funds belonging to the aggressive risk category: Equity Fund, Group Equity Fund, Second Stock Fund and İş Bank Equity Index Fund. Univariate time series methods such as ARIMA and exponential smoothing methods were used to develop forecasting models and compared with Naïve method.

This study offers many advantages for stakeholders. Firstly, it will indicate how pension mutual funds are likely to perform in the future. If a particular fund is expected to have low performance, its investment instruments can be diversified for the next year, or the proportions of the relevant investment instruments within the fund can be changed. Additionally, the management of high-yielding pension mutual funds will be an important tool in increasing the marketing capability of the relevant pension company's retirement products. Thus, reaching more customers and contributing to an increase in market share of the relevant pension company will be facilitated. Another benefit is that customers will be able to have an idea of where to direct their individual retirement investments. This could potentially lead to greater profits for them.

This study can pave the way for future research. For example, while this study examined investment funds with aggressive risk type, other studies could use pension mutual funds in different risk categories (conservative, balanced, or aggressive). On the other hand, while univariate time series were used in our study to develop forecasting models for pension mutual funds, multivariate time series methods (such as linear regression and artificial neural networks) could also be utilized. Additionally, the research conducted in this study could be applied to many investment instruments outside of the individual pension system (such as stocks, gold, or foreign exchange).

Funding

No funding was received for this work.

Credit authorship contribution statement

Simge Eşsiz: Investigation, Conceptualization, Data curation, Methodology, Software, Writing, Original draft preparation. **Muhammed Ordu:** Data curation, Original draft preparation, Validation, Supervision, Reviewing, Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

References

[1] Acer, A., Genç, T. & Dinçer, S. E. (2020). Türkiye'de faaliyet gösteren bireysel emeklilik şirketlerinin performansının Entropi ve COPRAS yöntemi ile değerlendirilmesi. *İstanbul Gelişim Üniversitesi Sosyal Bilimler Dergisi, 7(1),* 153-169.

[2] Alptekin, N. & Şıklar, E. (2009). Türk hisse senedi emeklilik yatırım fonlarının çok kriterli performans değerlendirmesi: TOPSIS metodu. *Dumlupınar Üniversitesi Sosyal Bilimler Dergisi, 25*, 185-196.

[3] Arslan, S. & Çelik, M. S. (2018). Türkiye'deki emeklilik yatırım fonlarının performanslarının BIST-100 endeksinin performansı ile karşılaştırılması. *İşletme ve İktisat Çalışmaları Dergisi, 6(4)*, 61-73.

[4] Ayaydın, H. (2013). Türkiye'deki emeklilik yatırım fonlarının performanslarının analizi. *Çukurova Üniversitesi Sosyal Bilimler Enstitüsü Dergisi, 22(2)*, 59-80.

[5] Aydın, Y. (2019). Türkiye'de hayat\emeklilik sigorta sektörünün finansal performans analizi, *Finans Ekonomi ve Sosyal Araştırmalar Dergisi, 4(1)*, 107-118.

[6] Bayrakçı, E. & Aksoy, E. (2019). Gri tahmin yöntemi: Bireysel emeklilik sistemi üzerine bir uygulama. *Avrasya Sosyal ve Ekonomi Araştırmaları Dergisi, 6(1)*, 20-33.

[7] Bollapragada, R., Savin, I. & Kerbache, L. (2013). Price forecasting and analysis of Exchange Traded Fund. *Journal of Mathematical Finance*, *3*, 181-191.

[8] BEFAS, (2024). *Pension Fund Trading Platform*. https://www.tefas.gov.tr/FonKarsilastirma.aspx?type=emk

[9] Çınaroğlu, E. (2022). Entropi destekli EDAS ve CODAS yöntemleri ile bireysel emeklilik şirketlerinin performans değerlendirmesi. *Anemon Muş Alparslan Üniversitesi Sosyal Bilimler Dergisi, 10(1)*, 325-345.

[10] Demir, G., Bircan, H. & Dündar, S. (2020). Bireysel emeklilik sistemindeki şirketlerin performanslarının gri ilişkisel analizle ölçülmesi ve bir uygulama. *Manisa Celal Bayar Üniversitesi Sosyal Bilimler Dergisi, 18(2)*, 155-170.

[11] Ege, İ., Karakozak, Ö. & Topaloğlu, E. E. (2016). Emeklilik yatırım fonlarının ELECTRE yöntemi ile performansının analizi. *Finans Politik ve Ekonomik Yorumlar, 614*, 59-68.

[12] Eken, M. H. & Gaygısız, H. (2010). Bireysel emeklilik şirketlerinde risk yönetimi ve Türkiye örneği. *Maliye Finans Yazıları, 1(88)*, 55-78.

[13] Ertuğrul, İ. & Öztaş, T. (2016). Bireysel emeklilik planı seçiminde karar verme yöntemlerinin uygulanması: COPRAS ve TOPSIS örneği. *Çankırı Karatekin Üniversitesi Sosyal Bilimler Enstitüsü Dergisi, 7(2)*, 165-186.

[14] Fan, W. (2022). Prediction of monetary fund based on ARIMA model. *Procedia Computer Science*, *208*, 277-285.

[15] Hyndman, R. J. & Athanasopoulos, G. (2014). *Forecasting Principles and Practice*. Otexts.

[16] Hyndman, R. J. & Khandakar, Y. (2008). Automatic time series forecasting: The forecast package for R'. *Journal of Statistical Software, 27*.

[17] Hyndman, R. J., Koehler, A. B., Ord, J. K. & Snyder, R. D. (2008). *Forecasting with Exponential Smoothing: The State Space Approach*. Springer.

[18] İlhan, B. (2021). Türkiye'de gönüllü katılım esaslı emeklilik yatırım fonlarının performans ölçümü: Emeklilik şirketi özelinde vaka analizi. *Akademik Hassasiyetler, 8(17),* 343-367.

[19] Kayakuş, M. & Terzioğlu, M. (2022). Yapay sinir ağları ve çoklu doğrusal regresyon kullanarak emeklilik fonu net varlık değerlerinin tahmin edilmesi. *Bilişim Teknolojileri Dergisi, 14(1)*, 95-103.

[20] Khashei, M., Torbat, S. & Rahimi, Z. H. (2017). An enhanced neural-based bi-component hybrid model for foreign exchange rate forecasting. *Turkish Journal of Forecasting, 1(1),* 16-29.

[21] Kirli Akin, H. & Ordu, M. (2022). A novel simulation-based two stage-optimization approach for nurse planning. *International Journal of Simulation Modelling, 21(4)*, 591-602.

[22] Korkmaz, T. & Uygurtürk, H. (2007). Türk emeklilik fonlarının performans ölçümünde regresyon analizinin kullanılması. *Uluslararası Yönetim İktisat ve İşletme Dergisi, 3(5)*, 37-52.

[23] Korkmaz, T. & Uygurtürk, H. (2015). Portföy optimizasyonunda Markowitz modelinin kullanımı: Bireysel emeklilik yatırım fonları üzerine bir uygulama. *Muhasebe ve Finansman Dergisi, (68)*, 67-82.

[24] Kuzu, Y. E. (2022). *Bütünleşik otoregresif hareketli ortalama (ARIMA) ve uyarlamalı ağ tabanlı bulanık çıkarım sistemi (ANFIS) yöntemleri kullanılarak enflasyon tahmini*, [Yüksek Lisans Tezi]. Yıldız Teknik Üniversitesi.

[25] Louisa, L., Fauzi, R., Nugraha, E. S. (2022). Forecasting of retirement insurance filled via internet by ARIMA models. *Journal of Actuarial, Finance and Risk Management, 1(1)*, 1–8.

[26] Makridakis, S., Wheelwright, S. C. & Hyndman, R. J. (1998). *Forecasting Methods and Applications*. John Wiley & Sons.

[27] Mutlu, Ö., Ordu, M. & Polat, O. (2016). Düşük riskli yatırımcılar için bireysel emeklilik sistemi ile banka vadeli mevduat sisteminin karşılaştırılması. *Alphanumeric Journal, 4(2)*, 95-114.

[28] Onocak, D. & Koç, S. (2018). Yapay sinir ağları ile emeklilik yatırım fonu hisse senedi fiyatlarının tahmini. *Finans Ekonomi ve Sosyal Araştırmalar Dergisi, 3(3)*, 590-600.

[29] Ordu, M. (2022). A simulation-based decision-making approach to evaluate the returns on investments. *International Journal of Simulation Modelling, 21(3)*, 441-452.

[30] Ordu, M. (2023, July). A Performance Analysis of Attack Individual Pension Funds by a System Dynamics Simulation Approach. 9th International IFS Contemporary Mathematics and Engineering Conference, Tarsus, Turkey (pp. 260-261).

[31] Ordu, M., Demir, E., Tofallis, C. & Gunal, M. (2023). A comprehensive and integrated hospital decision support system for efficient and effective healthcare services delivery using discrete event simulation. *Healthcare Analytics, 4*, 100028.

[32] Ordu, M. & Zengin, Y. (2020). A comparative forecasting approach to forecast animal production: A case of Turkey. *Livestock Studies, 60(1),* 24-31.

[33] Ozturk, C., Efendioglu, D. & Gulec, N. (2017). BIST 100 index estimation using bayesian regression modelling. *Turkish Journal of Forecasting, 1(2),* 66-71.

[34] Pension Monitoring Center, (2024). Gönüllü BES fonları. https://www.egm.org.tr/bireysel-emeklilik/gonullu-bes-fonlari/

[35] Sarsıcı, E., Değirmenci, B. & Öztürk, C. (2017). Sermaye piyasalarına yeni bir kavram olarak giren Türkiye varlık fonu yönetimi. *Balkan ve Yakın Doğu Sosyal Bilimler Dergisi, 3*, 51-58.

[36] Shen, M. (2022). Application of ARIMA and ETS Model in Fund Index Prediction. 2nd International Conference on Mobile Networks and Wireless Communications, Karnataka, India (pp. 1-4).

[37] Sindelar, J. (2019). Sales forecasting in financial distribution: a comparison of quantitative forecasting methods. *Journal of Financial Services Marketing, 24*, 69–80.

[38] Şahin, O. & Başarır, Ç. (2019). Bireysel emeklilik şirketlerinin finansal performanslarının değerlendirilmesi: Türkiye örneği. *Yönetim Bilimleri Dergisi, 17(33)*, 211-229.

[39] Ural, M. & Adakale, T. (2009). Bireysel emeklilik fonlarında risk yönetimi ve riske maruz değer analizi. *Ege Akademik Bakış, 9(4)*, 1463-1483.