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Advanced Algorithms for Designing and Creating Optimal Portfolios

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Abstract

Objectives: Achieving sustained and long-term economic growth requires efficient resource allocation. This research aims to enhance optimization methods based on Sharpe Ratio performance and introduce an intelligent trading method utilizing various algorithms.
Design/methodology/approach: A quantitative investment model is developed using the Momentum Algorithm and a long-term investment model over a six-year horizon. The model is applied monthly from 2019 to 2023 within the stock exchange framework. Additionally, a series of smart models (Overall Functions, Overall Mean, and Overall Algorithm with Kalman Filter) are created to determine capital amounts using intelligent patterns.
Findings: The findings demonstrate that the proposed structure outperforms conventional algorithms, indicating it can serve as a viable alternative for achieving superior investment outcomes.
Innovation: This research contributes to the existing literature by introducing advanced optimization techniques that leverage intelligent algorithms for trading strategies. The findings provide new insights into capital allocation efficiency and risk management in financial markets.

Keywords: Smart Portfolio, Momentum Algorithm, Kalman Filter, Kelly Creation.

1. Introduction

In recent years, numerous scientific activities have been conducted to educate the public on the analysis of financial markets and encourage them to invest and operate in these markets around the world. However, most traders are unable to use scientific analysis in transactions for many reasons. Therefore, there is a strong need for an automated approach to efficiently and effectively use financial data to support investment decisions (Amiri et al., 2016). One of the systems that have made significant efforts to improve is smart trading.

The key issue here is choosing the right investment strategy that results in the lowest possible risk while maximizing profits. In this research, a smart portfolio management approach is proposed to enhance existing methods. The proposed smart portfolio has a two-layer framework. In the first step, two quantitative investment models are implemented, each targeting a model over a different time horizon. Then, a set of smart models that allocate capital to quantitative models is created. The use of Kelly's criterion to create a smart portfolio is beneficial on several levels. First, it targets the patterns that occur in financial data across different time horizons, creating more reliable investment models and making better use of the data. In the second step, the maximum likelihood is calculated using Kelly's criterion at each step to determine the maximum return. Ultimately, investing in loss models is avoided, leading to a smart allocation of capital.

2. Theoretical foundations and research background

The relationship between asset return and risk has been the focus of many researchers and studies in recent decades. Such studies include the Sharpe (1964) and Black (1972) capital asset pricing models and the Fama and French three-factor model (Fama and French, 1993). Carhart introduced the four-factor model and added the momentum effect to the Fama and French models (Carhart, 1997). Other parameters, such as quality (Pietrovsky, 2000), liquidity (Einsteinbach, 2001), and volatility (Eng, Chen, and Jing, 2006), have been studied to identify additional return factors in active strategies. Technical analysis has examined the patterns of market trends and supply and demand for stocks (Achilles, 2000). Traditionally, optimization approaches have either used technical indicators (Hira Bayashi et al., 2009; Casano, 2010; Kaosik, 2012) or fundamental indicators (Hong et al., 2012) to rank shares and form portfolios to achieve greater returns (Pakizeh et al., 2017). Many different optimization methods based on metaheuristic algorithms have also been used, including simulated models (Krama and Skins, 2003), ant colonies (Dorrens et al., 2004), genetic algorithms (2008), particle swarms (Xav et al., 2011), and others.

Carlos Heitor et al. (2021) stated in a study entitled "Optimal portfolio strategies in the presence of regimes in asset return" that the approximation is shown to be fast and accurate in a four-regime setting with an allocation to four assets compared to the numerical solution developed in Guidolin and Timmermann (2007). The computation time of the approximate solution is shown to be practically independent of the number of assets when no predictors are present, and only marginally affected by the number of predictors. While the portfolio policy strongly depends on the current state of the economy, the consumption-to-wealth ratio is roughly state-independent. Predictability considerably changes the optimal portfolios. Hedging demands are negligible with regimes and no predictability, but are important with predictability. On the other hand, the consumption-to-wealth ratio is not very impacted by the predictor.

Wajid Reza and Ashraf (2018) studied the use of smart beta strategies and increased portfolio performance in Islamic investment. They stated that the introduction of smart beta strategies allows passive investors to compare the structure of equity securities using alternative strategies such as underlying weighting, equal amounts, and low-risk weighting strategies.

Saran Mehra et al. (2016) investigated the creation of smart portfolios using quantitative investment models. Using a large-scale historical dataset of stocks and indices, they showed that the K2 algorithm compares well-adjusted risks concerning Sharpe ratios, a better average price increase in comparison to average loss coefficients, and a higher probability of success in comparison to existing criteria. It also measures these indices in experiments out of sample.

Hitach and Zambrano (2016) examined the appropriate smart beta strategies for joint venture portfolios and stated that different smart beta strategies (such as weight, global variance, equal risk share, and maximum diverse risk) are presented as an alternative to index weight in the context of equity.

Chris et al. (2015) studied smart beta investment and stated that smart beta securities typically lead to a higher variety than capital market value metrics. But they still hurt the massive market downturn. Nieto et al. (2014) compared the OLS, GARCH, and Kalman filter methods on the Mexican Stock Exchange and found that the Kalman filter performs better than the other methods in estimating the beta coefficient.

Tehrani et al. (2018) performed portfolio optimization with the help of the Krill herd metaheuristic algorithm using different risk criteria on the Tehran Stock Exchange and stated that the Krill herd algorithm performs better than other conventional algorithms in finding efficient border and optimal portfolios and can be substituted for these methods to achieve better results.

Azizzadeh and Ebadi (2017) examined the choice of the optimal pair trading strategy under the statistical changes of the spread process and stated that proper investment and decision-making on the right position to buy or sell require a well-defined strategy.

Amiri et al. (2016) presented a smart trading model in financial markets based on genetic algorithms, fuzzy logic, and neural networks. In this study, they developed a smart trading system based on the well-known rules of technical analysis and the use of three tools: genetic algorithms, fuzzy logic, and neural networks.

Rahnamay Roodposhti et al. (2015) made an effort to optimize the portfolio using sustainable optimization, risk estimation, portfolio estimation, and comparison of risk and expected returns in this model with expected risk and returns in a classic model. It was found that the expected return on the portfolio in the sustainable model was not significantly different from the predicted return in the classic model, and the predicted risk in the sustainable model was not significantly different from the predicted risk in the classic model. However, by examining the return and risk of portfolios based on the weight provided by each model, it was found that the actual returns of both methods are not significantly different in the Iranian market. However, the real risk of a portfolio optimized by a sustainable model is lower than that of a portfolio optimized by the classical method.

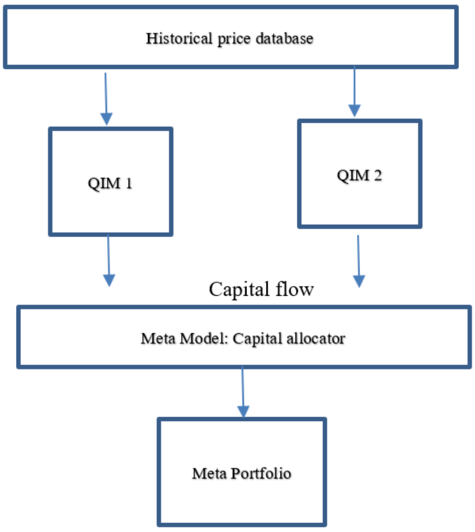
3 Research Method

3.1. Research objectives

The purpose of this study is to integrate models that distinguish various aspects of patterns and structures in data across different time horizons: long-run models to derive acceleration models and short-run models to derive the inverse mean. The process and underlying framework can be viewed as a two-way system: at the first level, models are tailored to concentrate on a specific aspect of financial time series, these models interact with the market and make business decisions. The second level involves a model that allocates capital to the first-level models and essentially creates a portfolio of quantitative models.

3.2 Conceptual model

Two quantitative investment models and several smart models will be implemented for the present study. These quantitative models were chosen because they operate at different times and are classified as assets that move inversely in the stock market. The proposed system for making trading decisions combines technical and fundamental techniques in stock selection and portfolio formation. The parameters used in the algorithms are optimized to maximize the return on the portfolio. The overall structure of the proposed system is as follows:



Historical Database: The database contains financial data in a time series of daily market prices, showing the high, low, and average prices per day of the dataset. These data support quantitative investment models and also aid in the analysis of all models and the daily valuation of securities.

Quantitative Investment Models: Quantitative models are simple investment methods in which the process is driven by an algorithm. Systematic and quantitative models mean that the start-up and implementation of an investment decision are completely controlled by an algorithm, eliminating human intervention.

Smart Model: The smart model involves dynamic allocation of capital. While data and analyses are updated daily, the smart model is designed to make capital allocation decisions at the end of each month.

Smart Portfolio: Represents the value of stocks in a portfolio resulting from the allocation of capital to the first investment model and the second investment model.

3.3. Regression model

Regression analysis begins with ordinary least squares for both models to determine the nature of the relationship between the two-time series.

$$yt = \beta xt + \varepsilon t \qquad (1)$$

The correlation between the model residuals and the Dickey-Fuller unit root test was analyzed using the ordinary least squares method. The normality test was conducted using the Jarque-Bera test. Additionally, the heteroscedasticity test was performed based on equation (2), which indicates the inverse behavior of the data and suggests that the variables are entirely stochastic.

$$VR(\tau) = \frac{\sum_t (\Delta^\tau y_t - \overline{\Delta^\tau y})^2}{\tau \sum_t (\Delta y_t - \overline{\Delta y})^2}. \qquad (2)$$

Where T is the long-run stock variance length, y_t is time series levels, and Δy_t is the daily variation in time series.

3.3.1 First model: the Kalman filter algorithm

The Kalman filter approach involves a set of mathematical equations that solve state and measurement equations simultaneously to obtain unobserved states. This method optimally estimates the values of the unobserved variables using information from the observed variables after minimizing the error. The Kalman filter is a recursive method for computing optimal estimations of the unobserved state vector based on the appropriate dataset. This method is applied to the state space model, and its algorithm provides a recursive solution to optimize the system described in the state space. This solution uses existing data to optimize previous data. The Kalman filter is a method in which models are directly corrected using mathematical models rather than saving all previous data to obtain subsequent data and correct the model. Mathematically, the state space equations in the

Kalman filter process are presented as follows for estimating X ∈ Rn state variables:

(Kalman filter algorithm input: price data, variance model, variance observations, and vector return output).

Algorithm 1: The Kalman Filter model

Algorithm 1 KALAMN FILTER Function: Input: price data, W = model variance, V=observation variance. Output: $\theta_{t|t.}$

Function KALMAN FILTER (Z_t)
If t = then
Initialize $\theta_{0|0} \leftarrow z_0$
Initialize $P_{0|0} \leftarrow 1$
End if
$\theta_{0|0-1} \leftarrow \hat{\theta}_{t-1|t-1}.$
$P_{t|t-1} \leftarrow P_{t-1|t} + W_t.$
$y_t \leftarrow \theta_{t|t} - \hat{\theta}_{t|t-1}.$
$S_t \leftarrow P_{t|t-1} + V_t.$
$K_t \leftarrow P_{t|t-1} S_t^{-1}.$
$\hat{\theta}_{t|t.} \leftarrow \hat{\theta}_{t|t-1} + K_t r_t.$
$P_{t|t} \leftarrow (I - k_t H_t) P_{t|t-1}$
Store $\theta_{t|t.}$ and $P_{t|t}$
Return $\theta_{t|t.}$
End Function

Where Z_t Є R^m represents the observation vector, H_t is the observation matrix, A_t is the system matrix That predicts our position in the next step, where Vt and Wt are observations and covariance matrix values of size (p*p) and (m*m), respectively. Finally, in the above algorithm, the kt coefficient is the Kalman coefficient, which must be chosen so that the error covariance is minimized, and the measurement is reliable.

The Kalman filter algorithm is a simple, scalable model where there is only one stock price variable. Given that the closing stock price (today's closing price at time t) is the best estimator for tomorrow's price (at time t + 1), the state model variable is a single set whose variance is estimated using monthly data at 72 points for each company. This model is based on the moving average (price) of the data. The next step is to use Algorithm 2. After updating the moving price average, it is checked whether the future trade's price is higher than the average or not. If the price is above the average, we will check if we have previously opened a position. If not, future (long) and open trades are purchased, and the portfolio is updated. If the price is below the moving average and there is no open position, a new position is opened by selling (short) and updating the portfolio.

3.3.2 Second model: momentum algorithm

After identifying the stocks, the initial statistical regression tests (normality, stationarity, non-linearity, autocorrelation, etc.) are run. These tests serve as an early indicator of the stability of relationships. Regression analysis reveals a relationship between the two time series. The regression residual indicates that the relationship can potentially be reversed. The Run's experiment provides an estimate of the time it takes for the residue to return and establish a correlation in the residue. VRT is also utilized to analyze the average return on dispersion, indicating the range on which the model can focus. Most importantly, VRP can be used to explore the return reversal on domains, the ultimate success threshold for an expansion that should be included in the portfolio.

Tests play a crucial role in identifying key features in data, models, and interval sizes. Model building and calibration are iterative processes as the optimal interval must be determined to maximize profits in transactions and portfolios, requiring identification of the average reversal rate and standard deviation measurement for the best returns.

After conducting initial tests using the Kalman filter algorithm and its output, the momentum algorithm is applied with daily future price inputs until a suitable portfolio utilizing the momentum pattern is achieved. The method by Jagadish and Titman (1993) is employed to execute and select the appropriate portfolio based on the Sharp Ratio criterion. Each company's stock is ranked monthly based on risk-adjusted criteria, and the average cumulative return on the portfolio is calculated to select the suitable portfolio using the momentum strategy. Stocks of companies are then chosen based on the Kalman filter pattern in terms of trading position. Finally, the appropriate portfolio model is developed based on the Kalman filter model, incorporating moving average, size, current price, cumulative return, and the company's stock position in the portfolio.

Algorithm 2: The momentum model

Algorithm 2 Momentum: Input x: Log of index futures, Output: Momentum model portfolio.

# READ daily futures prices as $x_{(n,t)}$, where t is the time stamp, n is the number of futures markets, and $x \in R$.
# rebalance () is a function that takes the current portfolio, computes the mean investment in the futures market, and buys and sells so that capital is equally divided among the futures markets.
# w=moving average window size
# $IIt=(II_{(1,t)}, II_{(2,t)}, \dots, III_{(n,t)}$, where $II_{(i,t)}=<C_{(i,t)},P_{(i,t)}>$
# $C_{(i,t)}$ is capital invested in futures contract I at time t
# $P_t=(II_{(1,t)}, II_{(2,t)}, \dots, III_{(n,t)})$ position in portfolio.
# $P_{(i,t)} \in \{Buy.Sell\}$ position of futures I at time t.
# KALMAN FILTER is the Kalman is the Kalman Filter Function as described in Algorithm 1.
For I = 1 to n do
$C_{(I,0)} \leftarrow$ investment / n
$P_{(I,0)} \leftarrow$ Buy
End for
For t = 1 to T do
$Ct \leftarrow$ rebalance (C_{t-1})
$P_t \leftarrow P_t$-1
For I = 1 to n do
$X_{(i,t)} \leftarrow$ get current price
$y_{(i,t)} \leftarrow$ KALMAN FILTER(x(i,t) # kalman filter prediction
$z_{(i,t)} \leftarrow$ moving average ($y_{(i,t)}$) $\frac{1}{w}\sum_{t-w} hy_{(i.t)}$
if $x_{(i,t)}>z_{(i,t)}$ then
if $P_{(i,t)}$!=Buy then
$P_{(i,t)} \leftarrow$ Buy
End if
Else
If $P_{(i,t)}$= != Sell them
$P_{(i,t)} \leftarrow$ sell
End if
End if
End if
End for

3.3.3 Third model: long-term strategy algorithm

In the long-term equity strategy, stocks are simply purchased. This means that stocks that are falling behind their peers in terms of moving average returns (according to financial theory, corporate stocks move in line with positive news in the group) are identified and purchased. The long-term stock strategy model is a stable model in which capital allocation is done equally, assuming that the beginning and end prices are obtained, and all trades are adjusted at the time of trading. In the first step, the stocks are arranged with their returns in descending order, and then the number of stocks is divided into two halves based on returns.

The top half consists of stocks with better performance than the bottom half. The stocks to be purchased are first determined, and the stocks in the upper half are purchased. Then, the stocks in the lower half are purchased. After that, the portfolio model is updated to allocate to all transactions in the next step. Specifically, stocks with the worst performance are purchased with the expectation that they will acquire other stocks with better performance.

Algorithm 3: Long-term strategy model

Algorithm 3 Long Only: Input E: Stock returns, Output: Long Only portfolio.

# READ stock returns prices as$\varepsilon_{(n.t)}$, where t is the time stamp, n is the number of stocks, and $\varepsilon_{(n.t)} \in$ R
# rebalance() is a function that takes the current portfolio, computes the mean investment in the futures market, and buys and sells so that capital is equally divided among futures markets.
# IIt=($II_{(1,t)}$, $II_{(2,t)}$, … , $III_{(n,t)}$), where $II_{(i,t)}$=<$C_{(i,t)}$,$P_{(i,t)}$>
# $C_{(i,t)}$ is capital invested in futures contract i at time t.
# C(t) is the capital value of the portfolio at t.
# P_t=($II_{(1,t)}$, $II_{(2,t)}$, … , $III_{(n,t)}$) position in portfolio.
# $P_{(i,t)} \in \{Buy.Sell\}$ position of futures I at time t.
# Let S be a set of sectors.
# Let s is a sector C S.
# Let ε be a set of equities iu sector S.
# Let e be single equity.
# Let £ be a set of laggard stocks in a sector.
# laggard() is a function that returns [$|\varepsilon|$/2], the worst-performing stocks a.t current time.
for i = 1 to n do
$C_{(I,0)}$ ← investment/n
end for
for t = 1 to T do
$C_{(t)}$ ← rebalance ($C_{(t-1)}$)
for s ∈ S do
$£_{(s,t)}$ ← laggard ($\varepsilon_{(s.t)}$)
For e ∈ ε_s do
Of $P_{(e,t)}$ = Own and e ∉ $£_{(s,t)}$ then
Sell $_{(e)}$
End if
End for
For e ∈ £s do
If $p_{(e,t)}$=Not-own then
Buy $_{(e)}$
End if
End for
End for
End for

3.3.4 Performance Curve Function

The performance curve function, as shown in Algorithm 7, represents the performance of every QIM based on an initial investment of 100 units using this formula
$PC_{(t-1,m)}$ * (1+($QIM_{(t,m)}$).

Here QIM represents the return on the model and PC represents the price. We will use the performance curve function in four models. Kelly with Kalman Filter, Median Kelly with Kalman Filter, Kelly with Moving Average, and Median Kelly with Moving Average.

Fourth model: Kalman Filter Function

The function attempts to forecast whether the QIM return in the next period is positive or negative.

The input to this model is the monthly performance of the QIMs. The function checks whether the forecast for (i+1) is positive or negative when compared to the previous time step. When the Kalman Filter forecast is negative, the signal is converted to 0 and when the forecast is positive the signal is 1. The reason we changed the forecast to binary data is to adjust the Kelly in the upcoming metamodels

Algorithm 4 PERFORMANCE CURVE Function: Input = QIM Returns, output Price, Performance curve of QIM.

READ QIM returns as $X_{(n,t)}$, where t is the time stamp and n is the number of QIM models.

price$_{(i,t)}$ is the value of the model indexed to 100

$$X = \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{tn} \\ X_{21} & X_{22} & \cdots & X_{tn} \\ \cdots & \cdots & \cdots & \cdots \\ X_{T1} & X_{T2} & \cdots & X_{tn} \end{bmatrix}$$

Price$_{(1:n,0)}$ ← 100
For t = 1 to T do
For I = 1 to T do
Price$_{(i,t)}$ ← price$_{(I,t-1)}$ × (1+x$_{(i,t)}$)
End for
End for
Return price

five models: Smart model

Now that the returns from the algorithms of quantitative investment models are calculated monthly, they are used in smart models to allocate capital. Therefore, the allocation of capital in the smart model is changed on a monthly basis. In this section, the smart model algorithm is designed to allocate capital to quantitative investment models using the Kalman filter algorithm and Kelly’s functions. The optimal amount of capital will be allocated to quantitative investment models. Then, based on Kelly’s criterion, the goal is to maximize the Sharpe ratio.

3.3.5 Kelly's criterion algorithm

Kelly's criterion has many desirable characteristics. First, it maximizes shareholder wealth without the risk of bankruptcy, and it maximizes the geometric mean, also known as the combined rate of return on investment. The rate of return is compounded, meaning it comes from returning capital from the previous period and remaining in an investment that can generate self-returns. Second, since Kelly is about reinvestment or a multi-period approach, an investor needs to maximize the geometric mean. Third, the estimated time to achieve the desired wealth is minimal with Kelly. Fourth, Kelly's strategy is shortsighted, meaning that only current investment opportunities and funds should be considered, not future conditions. Finally, Kelly's model allows investors to easily adjust their desired risk at lower expected return costs (McLean et al., 2011).

Since Kelly aims to maximize the wealth logarithm, optimal weights are calculated using equation (3):

$$max \sum_{t-1}^{T} log\left(\sum_{t-1}^{n} 1 + \left(w_{t(t)} r_{t(t)}\right)\right) \qquad (3)$$

Where r_i refers to the return on quantitative investment models and w_i is the maximum weight of the logarithm of wealth that weights are used to calculate portfolio returns at a future time (t + 1).

Algorithm 5: Kelly's functions algorithm

Algorithm 4 Fractional Kelly: Input = QIM returns, output = Portfolio returns.

READ QIM returns as $X_{(n,t)}$, where t is the time stamp and n is the number of QIM models.
$P_{(t)}$ s the value of the portfolio at l.
$II_{(t)}$ is portfolio at current time, , where $II_{(t)}$ = <$C_{(t)}$, $X_{(t)}$>/
$W_{(t)}$ are the weights to allocate capital to the QIMs.
$C_{(t)}$ iuvestrneut capital.
KELLY() is a fnnction described in Algorithm 5 that calcnlatc fractional Kelly weights for all the QIMs at t.
reallocate() is a function that changes the proportion of capital invested in different QIMs according to their weights, <$II_{(t)}$, $w_{(t)}$>.

$$X = \begin{bmatrix} X_{11} & X_{12} & \dots & X_{tn} \\ X_{21} & X_{22} & \dots & X_{tn} \\ \dots & \dots & \dots & \dots \\ X_{T1} & X_{T2} & \dots & X_{tn} \end{bmatrix}$$

$W_{(0)} \leftarrow 0$
$P_{(0)} \leftarrow 0$
$for\ t = 1\ to\ T\ do$
$w_{(t)} \leftarrow KELLY\ (x_{(t)})$
$c_{(t)} \leftarrow reallocate\ (II_{(t-1)}, w_{(t)})$
$p_{(t)} \leftarrow \sum_{i=1}^{n} x_{(i)} c_{(t)}$
end for

3.3.6 New smart model

In Kelly's criterion mean model, mean data is utilized. In the mean distribution algorithm, similar to the mean case, there is an alternative method to assess the central tendency of the distribution. However, when the data is not normally distributed, the mean distribution may not always be the best estimate of central tendency. Previous research on earnings forecasts has indicated that the mean can be a superior estimate in terms of performance. On the other hand, Kelly's criterion is a non-distributed approach and is inherently short-sighted. The objective of this algorithm is to demonstrate that the mean can outperform the Sharpe ratio and more accurately represent the central tendency distribution. This algorithm will function similarly to Kelly's model, with the exception that Kelly's criterion calculations will be based on the mean data while keeping other parameters constant. Portfolio returns are also computed based on the weighted returns of the quantitative investment models.

$$f^* = \frac{x-r}{\delta^2} \quad (4)$$

One of the major challenges in smart models is changing data regimes. If the pattern or structure has been paused for some time, a change in the data regime can lead to the loss of quantitative investment models. Potentially, to restart investment, a prudent portfolio manager wants to avoid a loss situation by allocating assets and also prefers a situation in which capital in particular will avoid losses. Preventing loss-bearing investments can improve Sharp returns and ratios. Kalman filter is used to prevent losses in investment in quantitative-specific investment models and focus on investments with potentially positive returns. The Kalman filter is also used to evaluate whether models have positive or negative returns in t + 1. The Kalman filter helps avoid negative forecast return periods, but invest using the forecast for positive returns. Kelly's criteria and Kalman filter functions were used to construct this model. At each stage, the Kalman filter predicts whether the quantitative investment models will have a negative or positive return. Quantitative investment models will be calculated as 1 for positive predictions and 0 for negative predictions. The quantitative investment model is eliminated by the negative predictions, and Kelly's criterion weight return will be recalculated using the number of quantitative investment models.

Algorithm 6: Kelly's mean algorithm

Algorithm 5 Median Kelly: Input = QIM returns, Output = Portfolio returns.

READ QIM returns as $X_{(n,t)}$, where t is the time stamp and n is the number of QIM models.
$P_{(t)}$ s the value of the portfolio at l.
$W_{(t)}$ are the weights to allocate capital to the QIMs.
$C_{(t)}$ iuvestrneut capital.
$II_{(t)}$ is portfolio at current time, , where $II_{(t)}$ = <$C_{(t)}$, $X_{(t)}$>
MEDIAN KELLY () is a function described in Algorithm 6, it calculates Median Kelly weights for all the QIMs at t.
reallocate () is a function that changes the proportion of capital invested in different QIMs according to their weights, <$II_{(t)}$, $w_{(t)}$>.

$$X = \begin{bmatrix} X_{11} & X_{12} & \dots & X_{tn} \\ X_{21} & X_{22} & \dots & X_{tn} \\ \dots & \dots & \dots & \dots \\ X_{T1} & X_{T2} & \dots & X_{tn} \end{bmatrix}$$

$W_{(0)} \leftarrow 0$
$P_{(0)} \leftarrow 0$
$for\ t = 1\ to\ T\ do$
$w_{(t)} \leftarrow MEDIAN\ KELLY\ (x_{(t)})$
$c_{(t)} \leftarrow reallocate\ (II_{(t-1)}.w_{(t)})$
$p_{(t)} \leftarrow \sum_{i=1}^{n} x_{(i)} c_{(t)}$
end for

Algorithm 7: Kelly's Criterion Algorithm with Kalman filter

Algorithm 6 Kelly uith Kaalan Filter: Input = QIM returns. Output = Portfolio returns.

READ QIM returns as $X_{(n,t)}$, where t is the time stamp and n is the number of QIM models.
$P_{(t)}$ s the value of the portfolio at l.
$W_{(t)}$ are the weights to allocate capital to the QIMs.
$C_{(t)}$ iuvestrneut capital.
$II_{(t)}$ is portfolio at current time, , where $II_{(t)}$ = <$C_{(t)}$, $X_{(t)}$>
reallocate () is a function that changes the proportion of capital invested in different QIMs according to their weights, <$II_{(t)}$, $w_{(t)}$>.
PERFORMANCE CURVE() is the function described in Algorithm 7. It con-verts QIM returns to price.
KELLY() is a function described in Algorithm 5 it calculates fractional Kelly weights
BIN ARY KALMAN FI LT ER() is a function described in Algorithm 8. It gives a binary output based, on the forecast from our Kalman Filter.

$$X = \begin{bmatrix} X_{11} & X_{12} & \dots & X_{tn} \\ X_{21} & X_{22} & \dots & X_{tn} \\ \dots & \dots & \dots & \dots \\ X_{T1} & X_{T2} & \dots & X_{tn} \end{bmatrix}$$

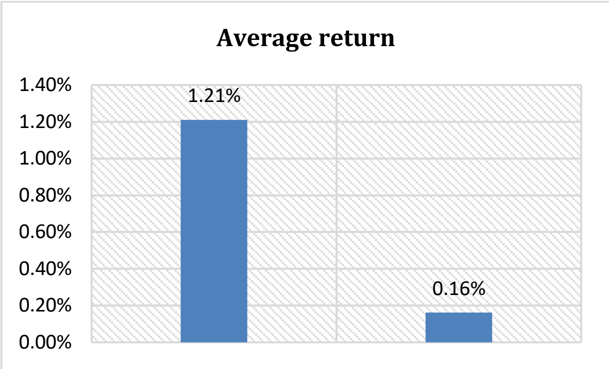
for t = 1 to T do
$Kell_{y(t)}$ = KELLY($x_{(t)}$)
Sum ← 0
for i = 1 to n do
$price_{(t,i)}$ ← PERFORMANCE CU RV E($X_{(t,i)}$)
if BINARY KALMAN FILTER($price_{(t,i)}$) 1 = 1 then
$Kelly_{(t,i)}$ = 0
end if
sum += $Kellv_{(t,i)}$
for i = 1 to n do
$Kelly_{(t,i)} = \frac{kelly_{(t.i)}}{sum}$
End for
End for
$W_{(t)}$ ← Kelly (t)
$C_{(t)}$ ← reallocate $(II_{(t-1)}.w_{(t)})$
$P_{(t)} \leftarrow \sum_{i=1}^{n} x_{(i)} c_{(t)}$
End for

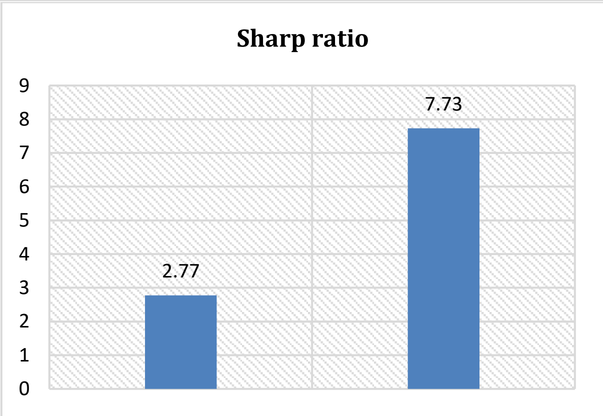
2 4. Results of model parameters and functions

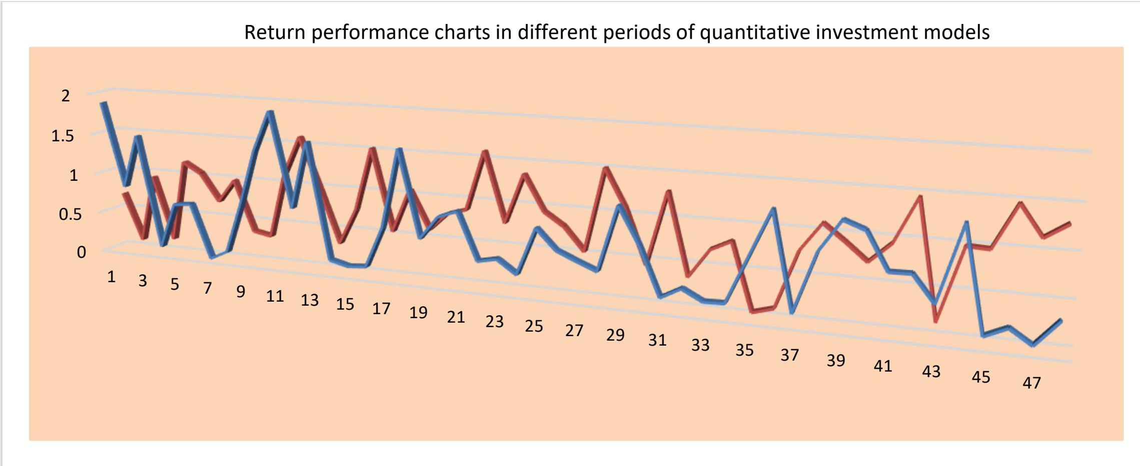
To create intelligent financial portfolios considering the parameters of companies operating in various industries on the Tehran Stock Exchange from March 2017 to March 2021, 18 companies were chosen for portfolio selection utilizing the Kalman filter algorithm, the momentum algorithm, a long-term strategy, and ultimately, a smart model based on Kelly's functions, Kelly's mean, and Kelly's criterion with the Kalman filter. The proposed algorithms were initially executed in Matlab software, and subsequently, the average return, average volatility, and Sharpe ratio were calculated and derived for quantitative investment models (momentum and long-term investment). The findings revealed that the mean returns and volatility in the long-term stock strategy exceeded those of the momentum model, contrary to the expected lower volatility in the long-term stock strategy. Additionally, the Sharpe ratio was negative in both models, indicating a negative return. The results of the algorithm performance are detailed in Table 1.

Table 1: Quantitative Investment Models' Performance

Description	Momentum	Long-term strategy
Average return	0.1624 %	1.21 %
Average fluctuations	0.01336 %	3.14 %
Sharp average ratio	7.73	2.77



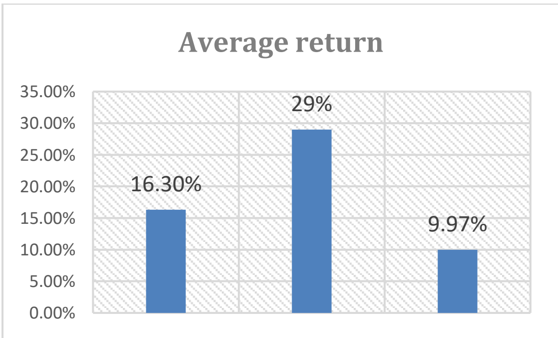


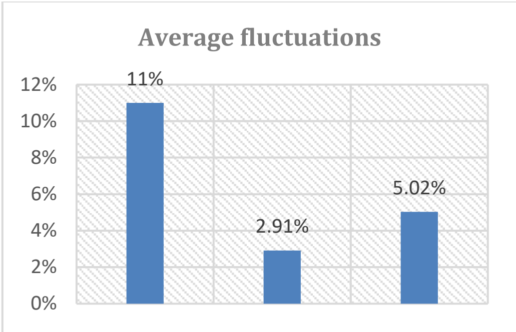


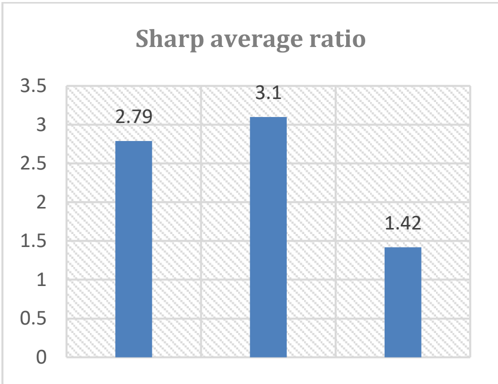
After implementing quantitative investment models, it is now time to focus on smart investment models that allocate capital to these quantitative investment models. The results of the smart model showed higher returns compared to the quantitative investment models, with the best Sharpe ratio and performance seen in the smart Kelly model. Analysing the Sharpe ratio in each application was very promising for the proposed smart model and framework, as the smart model demonstrated the highest efficiency and therefore the best Sharpe ratio. As shown in Table 2, the average return in Kelly's criterion is higher than all other models, indicating that this smart algorithm provides a good measure of investment and return based on Sharpe ratios and average volatility.

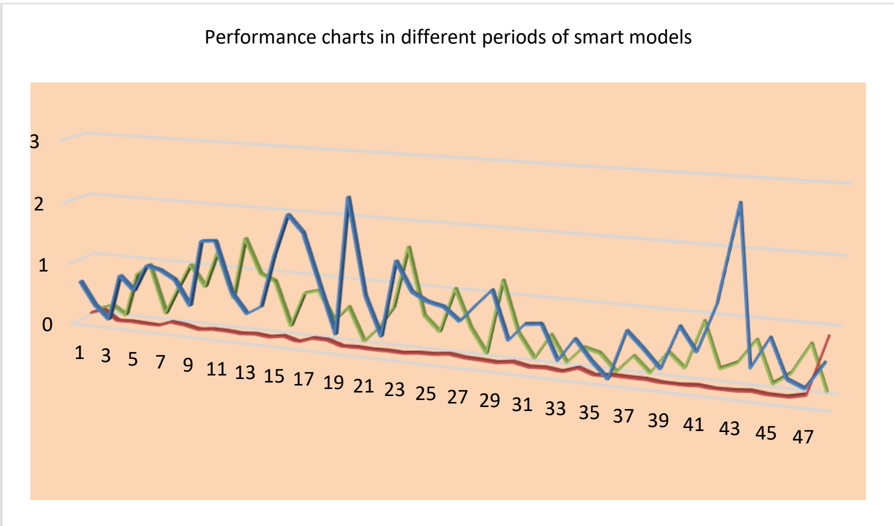
Table 2: Smart Models' Performance

Description	Kelly functions	Average Kelly functions	Kelly criteria with the Kalman filter
Average return	9.97 %	0.29 %	16.30 %
Average fluctuations	5.024 %	2.91 %	11 %
Sharp average ratio	1.42	3.1	2.79




Average fluctuations
12%
10%
8%
6%
4%
2%
0%
11%
2.91%
5.02%


Sharp average ratio
3.5
3
2.5
2
1.5
1
0.5
0
2.79
3.1
1.42


Performance charts in different periods of smart models
3
2
1
0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47

Based on the optimal values obtained, it is evident that Kelly's criterion algorithm demonstrated superior performance, higher efficiency compared to other models, and better Sharpe ratios. Additionally, a key strength of this model is its lower volatility in comparison to previous models, showcasing the stability of the algorithm. In conclusion, smart models that offer increased returns and lower risk are the most effective and efficient models available.

5. Discussion and Conclusion

This research aimed to propose a metaheuristic model for creating a smart financial portfolio on the Tehran Stock Exchange. The model utilized the Kalman filter and Kelly's function to form an optimal portfolio. To design the optimal and smart portfolio model, quantitative investment models were first used, including the momentum algorithm and the long-run investment algorithm. These models utilized technical indicators and fundamental ratios to select the optimal portfolio. Additionally, Kelly's function, Kelly's mean, Kelly's composition algorithms, and the Kalman filter were incorporated into the smart model.

Key parameters such as average returns, mean volatilities, and average Sharpe ratio were compared across the four different models over a 5-year period from 2019 to 2023. Data was extracted monthly and organized using Excel software. The years were categorized as periods of decline, equilibrium, and growth. Before designing the model, regression assumptions were analysed, including normality of the data, stationary state, non-heteroscedasticity, and non-linearity between the data.

The results indicated that the data was normal based on the Jarque-Bera test with an error level of less than 5%. Stationarity analysis was conducted using the Dickey-Fuller test, showing that all variables and parameters were stationary at a 99% confidence level. Additional statistical tests confirmed the efficiency and Sharpe ratio of the proposed smart Kelly algorithms outperformed other models. The average return, Sharpe ratio, and volatility in Kelly's criterion model were superior to all other models.

Ultimately, the Kelly criterion model demonstrated better performance than quantitative investment model algorithms. The value of the portfolio derived from the proposed Kelly algorithm exceeded that of other algorithms, highlighting the efficiency of the proposed algorithm and model. The results suggest that the smart Kelly models were more effective in selecting portfolio models. This demonstrates the efficacy of the proposed algorithm and model.

The performance of portfolios formed using the proposed algorithms consistently showed that the average return in Kelly's algorithm surpassed that of the momentum and long-run investment algorithms. These findings align with the results of Saran Mehran et al. (2016).

Researchers interested in conducting research in relevant areas are recommended to explore the following topics:

- Utilize various quantitative investment algorithms, including pair shares and market indexes.
- Develop objective functions that consider additional risk and performance metrics of the portfolio, and compare outcomes.
- Examine the impact of integrating other fundamental ratios and technical indicators into the algorithm structure.
- Assess the effects of different factors and investment styles, such as liquidity, trading volume, etc., on the model input.
- Investigate macroeconomic factors that influence capital asset price fluctuations.
- Conduct market segmentation by industry and conduct comparisons between different sectors.
- Utilize a larger statistical sample, among other suggestions.

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