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Optimizing Portfolio Based on Prospect Theory and Wavelet Transform

Hamidreza Moghaddam
Degree master
Department of industrial engineering and management systems
Amirkabir university of technology
Hrm375@gmail.com

Abstract:
The balance between risk and return is one of the issues raised in the investment area. Forming a stock portfolio is considered the simplest and most effective way to reduce investment risk and increase return on investment. In the present study, the index tracking model and the prospect theory optimization model were investigated using index tracking. The data were analyzed using wavelet transform . The results were examined after removing the high frequency of the data and two algorithms including genetic and gray wolf algorisms were used in this regard. A significant assumption is that the behavioral characteristics of the prospect theory model provide better negative protection than traditional methods for the portfolio selection problem. In this study, the computational results of the prospect theory model for the real data of the financial market of the Dow Jones index and its 30 stocks were examined. To improve and confirm the result, wavelet transform was used to analyze the high-frequency and low-frequency data. The prospect theory model with the reference point which is the index is compared with the index tracking model. A major limitation was implemented for base index tracking and prospect theory models. The primary results of this work are: The advantage of stock portfolio diversification is evident in the prospect theory model. The tendency to obtain higher returns than the index in the prospect theory model with the reference point of the index leads to better performance of this model in the bull market. However, it performed worse than the index tracking model in a bear market. Finally, to confirm the implementation of the model, this model was compared with Markowitz's initial model. The prospect theory model obtained a higher return.
Keywords: **Stock portfolio optimization, Prospect theory, Index tracking, Haar wavelet transform, Meta-heuristic algorithms**

Introduction
The balance between risk and return is one of the issues raised in the investment area. Forming a stock portfolio is considered the simplest and most effective way to reduce investment risk and increase return on investment (Abzari, 2007). An investor can review his investment portfolio at any time in the real world (Esadi, 2014). Thus, investment portfolio management strategies are mostly considered in multiple periods. Multi-period problems, introduced by Masin (1968) for the first time, are a more general state of single-period problems, so the investor seeks to optimize asset allocation in each period (Amiri, 2013) to maximize the utility of wealth in the last period (Bagheri, 2015). Such issues have several applications in the real world, such as asset and debt management, index tracking, and investment management (Jones, 2004).
The recent financial crisis has indicated the shortcomings of market tools such as low credit in investment decisions (Khatami, 2018). This issue can be shown by considering the negative attitude of investors toward assessing the real risk. They mostly follow only their intuition (Coello, 2004). In investment practice, the status of unaccounted risks is almost common (Fuller, 1995). Hence, investors should have a reliable mathematical tool to justify investment decisions. In the present study, we consider BPT as a tool that considers behavioral errors (Bagheri, 2012). BPT was presented by Shefrin and Sutman (2000). The primary idea of this theory is to maximize the value of the investor's stock portfolio in which several goals are met and these goals are in line with different levels of risk aversion (Davodi, 2017). BPT is based on two main theories: Security-Potential/Aspiration Theory (SP/A) and Prospect Theory (PT). The SP/A theory, which was developed by Lula Lopez in 1987, is a general choice risk framework (not only financial) and is not specified for the stock portfolio (Raei, 2011).

In today's world, people have different levels of risk tolerance. It is not possible to predict the profitability of assets due to the presence of various factors affecting them. These uncertainties in the market increase the importance of diversification in investment and allocating capital to a group of assets. For this reason, investment management issues have shifted from stock selection to the management of a portfolio of stocks in the past years. Before buying and selling any type of securities, the investment policy, constraints related to the level of expected profit, the level of risk tolerance, and other constraints should be determined (Gupta, 2013). One of the major concerns of investors in the capital market is the selection of shares in terms of profitability. It means a profitable and ideal investment. Ideal capital causes the economic growth of any country as it increases the wealth of shareholders. For this reason, the difference in the methods of selecting the stock portfolio in investment and the difficulty of decision-making has been addressed in the past years. The traditional methods of selecting the stock portfolio do not have the required efficiency. Thus, the application of the prospect theory has been welcomed.

A review of the articles indicated that none of them have investigated the effect of wavelet transform on optimization and have investigated the optimization methods separately. The present study was an attempt to calculate these values and check their effect on the optimized basket. Also, the cardinality constraints were not used as a constraint in the conducted studies and a meta-heuristic method was used for optimization in most of these studies. The present study attempted to overcome this shortcoming. To examine the optimal solution, two meta-heuristic algorithms were used to obtain the optimal solution for our model. In this project, genetic and gray wolf algorithms were used to better optimize the stock portfolio and to optimize the profit of the stock portfolio. Another innovation is seen in the data used in the project. In this section, wavelet transform is used for data analysis and high-frequency removal. The present study was an attempt to identify the potential benefits of the behavioral prospect theory model based on different market conditions compared to the portfolio optimization model such as the index tracking (IT) model. In this study, the PT model is used for several experimental data sets to find an optimal solution for the stock portfolio selection problem using index tracking settings. For this purpose, appropriate solution approaches are used for the prospect theory, i.e., the genetic algorithm, which considers the mathematical complexity of the research problem. In this study, the performance of these models with cardinality constraints will also be examined.

Wavelet transform

Wavelet transform is a powerful mathematical tool introduced to solve the shortcomings of Fourier transform for the analysis of non-linear data or data that have local behavior in time and frequency (Zhu, 2011). The wavelet transform from the base function is called the mother wavelet function. Translation and dilation (scale) are used to obtain time series components over time (Zhang et al., 2009). The larger the scale used, the more the basic wavelet is elongated and the analysis will be done on low-frequency components of information. On the contrary, the smaller the scale used, the more the basic wavelet is compressed and the analysis is performed on the high-frequency components. Bruzda (2010) investigated European markets using analyses of variance and covariance of wavelet and showed that for the wavelet correlation becomes zero and even negative in some cases short-term investments. Wadi and Tahir Ismail (2011) used Haar and Daubchies Haar wavelets in predicting a market return in Oman's capital market. Using wavelet approximation series and the ARIMA model, they showed that wavelet approximation series data have more stable variance than normal return data and are more suitable for prediction (Chang, 2020). In an article entitled "Denoising the option price with the wavelet method", Hwang et al (2012) examined denoising the implied volatility using the wavelet transform and then determined the option price using the Black-Scholes model. Then, they compared the prices with the real data. The results indicate an improvement in prediction accuracy using denoised data.

Prospect theory

Based on this theory, investors are risk-averse as long as they earn profits, and their utility graph is ascending and descending. However, when they make losses, their risk tolerance will increase. Prospect theory states that people may not necessarily analyze information based on rational assumptions. Based on this theory of equal amount of loss and profit, the negative effect of loss on the investor is more than the positive effect of making a profit. Accordingly, he unconsciously considers the same concept in his choice. Most people want to have a reasonable return (even if there is a chance of a higher return). They want to reduce the risk of their trade so that they incur the minimum loss. In other words, loss has more weight in people's minds than the same amount of profit. Prospect theory is explained by the value function. The value function is an S-shaped curve that has a reference point. The reference point determines whether investors are risk-takers or risk-averse in such a way that investors are risk-takers below the reference point are risk-averse below it (Mansini, 1999).

Nadine Gatzert (2020) stated that the optimization of securities is a permanent issue in mathematical optimization and management sciences. Given the current conditions of the financial market with low-interest rates and unstable stock markets, the expansion of portfolio optimization models with other types of investments becomes more significant than classic assets. In this article, they presented a stochastic multistage mixed model that includes investment opportunities in irreversible and long-term infrastructure projects in the field of renewable energy, which are also subject to policy risk (Tsung-Jung, 2011). Alishahi and Azami (2018) stated that despite the growing use of portfolios and their rich literature, there are still many unanswered questions in this field. Results show that the use of innovative methods positively and significantly affects the selection and optimization of the stock portfolio of companies listed on the Tehran Stock Exchange.

In a study entitled “Optimizing the stock portfolio using the meta-heuristic algorithm of shrimp categories using different criteria of risk in the Tehran Stock Exchange”, Tehrani, Fallah Tafti, and Asefi (2018) showed that the algorithm of shrimp categories has a better performance to find the efficient frontier and optimal portfolios compared to other conventional algorithms it and can be replaced by these methods and achieve better results. Mesghari and Namdar Zanganeh (2013) evaluated several separate and conflicting objectives in selecting a stock portfolio among the many stocks offered in the stock market. For this purpose, based on different criteria, they first presented stock measurement and analysis indices. Then, by using non-linear mathematical modeling of integers and using artificial intelligence methods such as non-dominated genetic algorithms and Multiple Objective Particle Swarm Optimization algorithms, they evaluated the model performance. The results show that it is possible to achieve optimal performance in different sizes based on the use of these two algorithms (Zaboli, 2016).

Methods

The present study is applied in terms of aim and quasi-experimental. In this study, the data of the Dow Jones index and the stocks related to the Dow Jones index from 2015 to 2022 (half of 2022) and its related stocks, which have 30 stocks, were used. The data are generally classified into several parts: annual data, data used for the bull market, and data for the bear market. In this study, based on the division of each of the desired trends, both models are examined. The used data used were collected from the investing.com site and the Federal Reserve (Central Bank of America) site. To implement the models and the algorithms, MATLAB software was used. Wavelet transform was also done in MATLAB software. First, the data were analyzed using wavelet transform and two methods were used to implement the model: using the entire data to implement the model and removing the high signal, and implementing the model again. In this study, a basic article entitled "Optimization of stock portfolio using prospect theory" written by Grishina et al. (2016) was used.

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Models

In this section, the two optimization models are explained. The first model is the optimization model through index tracking and the second model is the prospect theory model through index tracking. Cardinality constraints were used in both models

Index Tracking Model (IT)

In this study, we use the simple index tracking model in a full matching mode, as we minimize the TE to reduce the difference between the return on the capital of the index and the return on the stock portfolio.

Consider at time s

ms- Index capital return

$o_s = \max(r_s(x) - rm_s, 0)$ = The higher rate of return on capital of the stock portfolio compared to the return on capital of the index

$u_s = \max(rm_s - r_s(x), 0)$ = The lower rate of investment return on the stock portfolio compared to the investment return on the index

TE for a given period is $|r_s(x) - rm_s|$. At time s, os, or us is zero. In other words, we can define a new value

$$\mathrm{TE}_s = o_s + u_s = \begin{cases} if\ o_s, o_s \geq 0 \\ otherwise\ u_s \end{cases} \qquad (1)$$

We define TE in the simplest possible way: the difference between the returns of the stock portfolio and the index over all periods s=1,…,S:

$$\mathrm{TE} = \sum_{s=1}^{S} \mathrm{TE}_s \ (2)$$

Here, TE can be defined in different ways. For example, TE can be defined as the square root of the mean difference between the returns of the index and the stock portfolio.

We can use the formulation of the model with cardinality constraint for the basic model by setting K=N. Thus, the index tracking problem with cardinality constraint can be formulated as follows:

$$minimizing\ \mathrm{IT_{cc}}(x) = minimizing\ \mathrm{TE}(x) = \sum_{s=1}^{S} (o_s + u_s) \qquad (3)$$

Subject to constraints

$$\sum_{i=1}^{N} \omega_i r_{is} = rm_s + o_s - u_s, s = 1, \ldots S \qquad (4)$$

$$\sum_{i=1}^{N} \omega_i = 1 \qquad (5)$$

$$I_i \varphi_i \leq \omega_i \leq u_i \varphi_i, i = 1, \ldots, N \qquad (6)$$

$$\sum_{i=1}^{N} \varphi_i \leq K \qquad (7)$$

$$\varphi_i \in \{0,1\}, i = 1, \ldots, N \qquad (8)$$

$$\omega_i \geq 0, i = 1, \ldots, N \qquad (9)$$

$$o_s, u_s \geq 0, s = 1, \ldots, S \qquad (10)$$

Equation (4) examines the difference between the returns of the optimal stock portfolio and the index for each period. Based on Constraint (5), the sum of investment weights should be equal to one (budget constraint). Constraint (6) describes the purchase threshold and limits asset investment. If asset I is not kept, i.e. φi=0, the corresponding weight ωi=0. If the asset i is kept i.e.

φi=1, (6) ensures that the value of ωi is between the appropriate lower and upper intervals of l_i and u_i, respectively. Constraint (7) ensures that the number of assets in the optimal portfolio is at most K. The definition of zero and one (8) reflects the acceptance (or rejection) of an asset in the portfolio.

Prospect theory model for index tracking (PT+IT)

Based on the prospect theory, it is necessary to obtain the standard utility function in the utility function of the prospect theory by using r,p. For this purpose, we transform the general r, p into the probability weight function of prospect theory π (p) and the value function v(r). The value function v(r) and the probability function π (p) have been defined. In this study, for easier calculation, the probability function π (p) is ignored and only its occurrence probability (P) is used.

The utility function of prospect theory can be written as follows in terms of π and v:

$$\mathrm{PT_U} = \sum_{s=1}^{S} \pi(p_s) v(r_s) = \sum_{s=1}^{S} p_s v\left(\sum_{i=1}^{N} r_{si}\omega_i\right) \qquad (11)$$

The utility function of prospect theory (11) is non-linear function. The goal of the prospect theory model is to find the optimal stock portfolio that maximizes the utility function of prospect theory and the decision variables are the weights of the available assets ω subject to constraints on the desired level of return on capital (in the case of the basic prospect theory problem formulation), funding, and borrowed sales. This is a non-linear and non-convex optimization model since the objective function is non-linear and non-convex.

The prospect theory portfolio selection problem is as follows (basic prospect theory model):

$$\text{maximizing } \mathrm{PT(x)} = \sum_{s=1}^{S} p_s v\left(\sum_{i=1}^{N} r_{si}\omega_i\right) \qquad (12)$$

Subject to constraints

$$\bar{r}(x) = \sum_{i=1}^{N} \bar{r_i}\omega_i \geq d, \qquad (13)$$

$$\sum_{i=1}^{N} \omega_i = 1, \qquad (14)$$

$$\omega_i \geq 0, i = 1, \dots, N \qquad (15)$$

By studying the prospect theory problem, we found that the principle of the model is very similar to the principle of the index tracking stock portfolio optimization problem.

We also implemented a cardinality constraint in this model to show the diversity of the stock portfolio. Not only are IT and PT compared with index tracking problems, but also these models are compared with a constraint on the number of assets in the portfolio. We formulate the perspective theory model with index tracking and cardinality constraint as follows:

$$\text{maximizing } \mathrm{PT} + \mathrm{IT_{cc}}(x) = \sum_{s=1}^{S} p_s v\left(\sum_{i=1}^{N} r_{si}\omega_i, rm_s\right) \qquad (16)$$

Subject to constraints

$$\sum_{i=1}^{N} \omega_i = 1, \qquad (17)$$

$$l_i\varphi_i \leq \omega_i \leq u_i\varphi_i, i = 1, \dots, N \qquad (18)$$

$$\sum_{i=1}^{N} \varphi_i \leq K, \qquad (19)$$

$$\varphi_i \in \{0,1\}, i = 1, \dots, N \qquad (20)$$

Where

$$v(r(x), rm_s) = \begin{cases} if\ (r(x) - rm_s)^{\alpha}, r(x) \geq rm_s \\ if\ -\lambda(rm_s - r(x))^{\beta}, \quad r(x) < rm_s \end{cases} \quad (21)$$

Wavelet transform

Wavelet transform was used to analyze the data and separate the high frequency of the data. For this purpose, Haar wavelet transform was used and the data were analyzed up to one stage. Wavelet transform is done through MATLAB and generates two new data series from the original data. High-frequency and low-frequency data indicate details and the primary nature of a series of data, respectively.

$$\psi(t) = \begin{cases} 1 & 0 \leq t < 1/2 \\ -1 & 1/2 \leq t < 1 \\ 0 & otherwise \end{cases} \quad (22)$$

The scaling function is equal to:

$$\phi(t) = \begin{cases} 1 & 0 \leq t < 1 \\ 0 & otherwise \end{cases} \quad (23)$$

Meta-heuristic algorithm

The genetic algorithm is one of the algorithms used in this study. The gray wolf algorithm is another algorithm used in this study. It is a stochastic and nature-based algorithm that models the hierarchical behavior of wolves and uses that model to predict and optimize the answer.

Parameters

1-Index tracking model

Tracking error=TE

2-Prospect theory model

Coefficient of risk aversion compared to profit α=0.88

Coefficient of risk aversion to loss = 0.88 ß

Coefficient of loss aversion λ = 2.25

Lower interval = 0.01 Li

Upper interval Ui =1

The coefficient of risk aversion in the loss area is δ = 0.61

The coefficient of risk aversion in the profit area is γ=0.69

In the prospect theory model, the above parameters are used, all of which are assumed to be fixed numbers and equal to the stated value. These values are based on the data in the original article as well as Kahneman's article.

Results

First, the data were analyzed and then the analyzed data were examined in a separate table. Then, two stock portfolio optimization models were examined through index tracking and prospect theory (without cardinality constraints and wavelet transform). TE, TEO, and, TEU variables were used to compare these two models. The data were used in one-year intervals and for each year from the beginning of 2018 to 2021. PT utility function was used to compare two algorithms in optimizing the prospect theory model. For this comparison, the number of iterations in the gray wolf algorithm was set equal to the number of generations in genetics, and the number of searches in gray wolf was set equal to the number of populations in the genetic algorithm to give an opinion about the efficiency of these two algorithms in optimizing the prospect theory.

Table 1: Statistical characteristics of the used data

Data set	Mean (10^{-3})	Variance (10^{-3})	SD	Skewness	Kurtosis
2021	0.75	0.06	0.0078	-0.402	0.7869
2020	0.23	0.54	0.0233	-0.826	9.261
2019	0.80	0.06	0.0078	-0.667	3.335
bull	0.94	0.10	0.0104	4.586	46.80
bear	-0.02	0.56	0.0238	0.243	5.110

Table 2: Statistical characteristics of analyzed data

Data set	Mean (10^{-3})	Variance (10^{-3})	SD	Skewness	Kurtosis
2021	0.72	0.04	0.0065	-0.037	2.987
2020	0.02	0.29	0.0171	-0.475	11.17
2019	0.95	0.22	0.0151	-1.996	16.34
bull	0.95	0.07	0.0084	2.277	16.78
bear	-0.03	0.07	0.0026	7.117	8.18

Table 3- Performance of algorithm and gray wolf algorithms

MODEL	PT	TE
GW	1.2950	0.3185
GA	1.1103	0.2459

Based on Table 3, it can be stated that optimization with gray wolf has fewer tracking errors. To better compare these two methods, we set the number of generations in the genetic algorithm equal to the number of iterations in the gray wolf algorithm and set the population number in genetics to the number of searchers in the gray wolf.

Table 4: Performance of the prospect theory and index tracking with index tracking problem in 2021

Data set	Model	Algorithm	N	TE	TE o	TE u
2021	IT	gw	25	1.0776	0.5491	0.5284
	PT+IT	gw	25	0.2790	0.1274	0.1515
	IT	ga	25	0.8141	0.4177	0.3963
	PT+IT	ga	20	0.2943	0.1423	0.1520

Table 5: The performance of the prospect theory model and index tracking with the index tracking problem in 2020

Data set	Model	Algorithm	N	TE	TE o	TE u
2020	IT	gw	25	0.1766	0.1004	0.0761
	PT+IT	gw	25	0.3207	0.1298	0.1909
	IT	ga	25	0.1848	0.0991	0.1848
	PT+IT	ga	20	0.2724	0.1123	0.1601

Table 5 reports the performance of both index tracking models and prospect theory using the genetic and gray wolf algorithms. In this method, it can be seen that the performance of the prospect theory model is weaker in both the tracking error and the portfolio return.

Table 6: Performance of the prospect theory and index tracking with the index tracking problem in 2019

Data set	Model	Algorithm	N	TE	TE o	TE u
2019	IT	Gw	25	0.1785	0.0901	0.0884
	PT+IT	Gw	25	0.3111	0.1396	0.1140
	IT	Ga	25	0.1480	0.0831	0.0648
	PT+IT	Ga	17	0.2994	0.1397	0.1597

In Table 6, only the data from 2019 were used as input data. In this section, it can be seen that the performance of the prospect theory method is significantly better than index tracking. However, the tracking error is still higher than this method.

Table 7: Performance of prospect theory and index tracking with the index tracking problem in 2018

Data set	Model	Algorithm	N	TE	TE o	TE u
2018	IT	gw	25	0.1353	0.0659	0.0693
	PT+IT	gw	25	0.3559	0.1880	0.1678
	IT	ga	25	0.1496	0.0775	0.0720
	PT+IT	ga	20	0.3120	0.1487	0.1633

In Table 7, which is based on the data of 2018, two models were implemented. It can be seen that the results, both in terms of profitability and in terms of tracking error, are not favorable in the prospect theory method and are far from the index tracking optimization method.

Table 8: Performance of prospect theory and index tracking with index tracking problem in 2021 (wavelet transform)

Model solution method	Model	Algorithm	N	TE	TE o	TE u
Gray wolf algorithm	IT	Original data	25	1.0776	0.5491	0.5284
	IT	Denoised	25	0.1273	0.0652	0.0620
	PT+IT	Original data	25	0.2790	0.1274	0.1515
	PT+IT	Denoised	25	0.1361	0.0522	0.0838
Genetic algorithm	IT	Original data	25	0.8141	0.4177	0.3963
	IT	Denoised	25	0.0778	0.0391	0.0778
	PT+IT	Original data	20	0.2943	0.1423	0.1520
	PT+IT	Denoised	18	0.1144	0.0405	0.0737

Table 9: Performance of prospect theory and index tracking with index tracking problem in 2020 (wavelet transform)

Model solution method	Model	Algorithm	N	TE	TE o	TE u
Gray wolf algorithm	IT	Original data	25	0.1766	0.1004	0.0761
	IT	Denoised	25	0.1765	0.1050	0.0709
	PT+IT	Original data	25	0.3207	0.1298	0.1909
	PT+IT	Denoised	25	0.3386	0.1413	0.1972
Genetic algorithm	IT	Original data	25	0.1848	0.0991	0.1848
	IT	Denoised	25	0.1799	0.0951	0.0847

Model solution method	Model	Algorithm	N	TE	TE o	TE u
	PT+IT	Original data	20	0.2724	0.1123	0.1601
	PT+IT	Denoised	19	0.2488	0.1016	0.1471

Table 10: Performance of prospect theory and index tracking with index tracking problem in 2019 (wavelet transform)

Model solution method	Model	Algorithm	N	TE	TE o	TE u
Gray wolf algorithm	IT	Original data	25	0.1785	0.0901	0.0884
	IT	Denoised	25	0.0674	0.0344	0.0329
	PT+IT	Original data	25	0.3105	0.1391	0.1714
	PT+IT	Denoised	25	0.1456	0.0575	0.0880
Genetic algorithm	IT	Original data	25	0.1480	0.0831	0.0648
	IT	Denoised	25	0.0660	0.0412	0.0248
	PT+IT	Original data	17	0.2994	0.1397	0.1597
	PT+IT	Denoised	15	0.1648	0.0701	0.0947

In three tables (10), the data of 2021, 2020, and 2019 for both the index tracking model and the prospect theory model have been examined through index tracking through genetic and gray wolf algorithms. The data were classified into two categories high-frequency and low-frequency data through wavelet transform. Examining the results revealed that the tracking error decreases after wavelet transform. It is evident in both methods and both algorithms. It means that the analyzed data follow a closer trend compared to the index and give better results.

Conclusion

In this study, the behavior-based model was examined. It is called the prospect theory model with index tracking. We compared it with the index tracking method through comparative analysis to better distinguish the differences. To examine the advantages of the behavioral approach, we implemented the cardinality constraint in this model. To obtain the best optimal solution, were used two algorithms, gray wolf and genetic. Finally, we analyzed the data to examine the studied data and classified the data into two parts: high-frequency and low-frequency. The results were analyzed using simulation in both bull and bear markets. The application of prospect theory with the index tracking model for the stock portfolio optimization problem shows that this model achieves a higher return on investment compared to the index tracking model. This issue can be explained by the turning point effect. Prospect theory tends to cross through the turning point as much as possible (for example, the risk-free rate) which reflects psychological biases. This turning point directs the model to select assets with a higher return on investment, regardless of the desired level of return on investment for the entire period.

The gray wolf algorithm obtains a better utility function for the prospect theory model and requires less time for calculation in a state in which the parameters of both algorithms are equal. The gray wolf tends to select a larger number of stocks and often selects the maximum cardinality constraint. On the contrary, the genetic algorithm tends to select a smaller number of stocks and rarely selects the maximum number. Regarding the stock market in 2018-2021, the models of the prospect theory model based on the index tracking of the return on investment more returns than the index tracking. Hence, it can be concluded that the optimal stock portfolios of the prospect theory performed better in the bull market than the index tracking model and the index itself in terms of return on investment. However, the PT model was slightly worse in the bear market compared to the index tracking model. It was also found that the PT model with IT is typically less diversified than the IT model (especially in the genetic algorithm), which is an advantage in terms of transaction costs and portfolio management issues.

Using wavelet transform indicated that all the data direct the trend of stock portfolios toward the index. It is desirable when the portfolio has a weaker performance than the index, and it is undesirable when the portfolio has a much more positive trend than the index and we avoid it. As an idea for future studies, a more intelligent selection of assets in the stock portfolio in the stage of reproduction of the genetic algorithm based on the observations and preferences of the studied model can be recommended. In each generation, the assets included in the best portfolio are distinguishable and this information is used for the reproduction step in the next generation.

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