

Comparative Analysis of Weighted Average and Ordered Weighted Average Methods for Stock Portfolio Optimization

Shruti Rathod¹, Harsh K Shah², Piyush Kapadiya³

^{1,2,3}Assistant Professor

^{1,2}Department of Science and Humanities, LDRP Institute of Technology & Research,
KSV University, Gandhinagar – 382015, Gujarat, India

³Department of Electronics and Communications, LDRP Institute of Technology and Research, Kadi Sarva
Vishwavidyalaya University, Gandhinagar, Gujarat, India

shruti_sh@ldrp.ac.in, harsh_sh@ldrp.ac.in, piyush_ec@ldrp.ac.in

Abstract - In light of the escalating market fluctuations and intricate investor inclinations, the identification of optimal equities necessitates analytical paradigms that integrate diverse decision-making criteria. This research employs multicriteria decision-making frameworks to assess and rank six publicly listed corporations according to six principal investment parameters: expected return, risk profile, liquidity, volatility, and alignment with market trends ESG scores. By employing both the weighted sum model and ordered weighted averaging aggregation techniques, we develop a decision matrix and extract comparative scores for each equity. The weights assigned to the criteria were determined based on two different approaches with a particular focus on return and risk. The findings reveal that although both WSM and OWA yield similar rankings for high-performing equities, subtle distinctions underscore the influence of operator sensitivity to score distribution. This research enriches the financial decision-making corpus by demonstrating how computationally straightforward yet analytically robust models can facilitate systematic portfolio selection.

Key Words: Aggregation operator, Weighted average, OWA operator, Portfolio selection.

1. INTRODUCTION

The process of making investment decisions within financial markets is intrinsically intricate, necessitating that investors assess a multitude of often discordant criteria, including anticipated returns, risk exposure, liquidity, volatility, and congruence with overarching market trends. Conventional stock selection techniques frequently depend on isolated metrics—such as return on investment or price-to-earnings ratios—that inadequately reflect the multifaceted characteristics of financial decision-making in contemporary markets. As the quantity and detail of market data continue to expand, there exists an urgent requirement for decision-support frameworks that are not only informed by data but also adept at incorporating investor preferences and real-world trade-offs.

Multicriteria Decision-Making (MCDM) models present a methodical and transparent strategy for addressing such complexities. These methodologies facilitate the concurrent evaluation of both quantitative and qualitative criteria, which aligns effectively with the intricate demands of portfolio selection and asset assessment. Among the array of Multi-Criteria Decision-Making (MCDM) methodologies, aggregation operators such as the Weighted Sum Model (WSM) and Ordered Weighted Averaging (OWA) serve as formidable instruments for the synthesis of heterogeneous criteria into a singular evaluative metric. WSM accentuates the relative significance (weights) of criteria, rendering it particularly appropriate for decision-making scenarios in which the importance of criteria is distinctly articulated. Conversely, OWA prioritizes the ordinal arrangement of values and incorporates a degree of flexibility in the modelling of optimistic or pessimistic tendencies in investor conduct.

This research investigates the application of MCDM frameworks and aggregation operators in the appraisal of investment alternatives within the stock market. More specifically, it utilizes WSM and OWA to evaluate six distinct stocks against five critical financial parameters. By contrasting the rankings produced through these methodologies, the research endeavors to elucidate both the coherence and discrepancies that emerge from employing various aggregation strategies. The results not only underscore the utility of MCDM in investment-related contexts but also provide valuable insights into the manner in which differing operator logics can shape financial decision-making outcomes.

This paragraph presents the outline for the remaining part of the document. Section 2 provides a brief explanation of the basic concepts of averages and the OWA operator. Furthermore, Section 3 introduces the case study of utilization of the OWA in the stock selection from retail and consumer Sector. Finally, in Section 4, the paper presents its main findings and conclusions.

2. PRELIMINARIES

This section covers throughout the concepts of aggregation operators, weighted averages, and ordered weighted averaging operators.

2.1. AGGREGATION OPERATORS

Aggregation operators represent a fundamental class of mathematical functions designed to combine multiple inputs into a single representative output, playing a crucial role in multi-criteria decision-making processes. These operators emerged from early work in fuzzy set theory pioneered by Zadeh (Zadeh, 1965). The theoretical foundations were solidified by Dubois and Prade (Dubois & Prade, 1985) through their work on fuzzy connectives and Yager's introduction of the Ordered Weighted Averaging operator (Yager, 1993), which represented a breakthrough in capturing decision-maker attitudes within the aggregation process.

A mapping $f: [0, 1]^n \rightarrow [0, 1]$, $n > 1$ is called an aggregation operator if it satisfies the following properties,

- (i) $f(0, 0, \dots, 0) = 0$, $f(1, 1, \dots, 1) = 1$ (both n times)
- (ii) $x \leq y \Rightarrow f(x) \leq f(y)$ for all $x, y \in [0, 1]^n$.

Aggregation operators satisfy additional properties, including symmetry, idempotence, associativity, and reflexivity. Understanding the core principles of aggregation operators is essential for researchers and practitioners in many disciplines. These operators offer a methodical, mathematical basis for combining and analyzing complex data, enabling better decision-making and thorough analysis.

2.2. WEIGHTED AVERAGE

The Weighted Average (WA) aggregation operator represents one of the earliest and most fundamental methods for combining multiple criteria into a single decision value. Dating back to the work of Kolmogorov (Kolmogorov, 1930) on generalized means, this operator has become a cornerstone of multi-criteria decision analysis due to its intuitive interpretation and computational simplicity.

A weighted average (WA) operator is denoted as $WA: R^n \rightarrow R$, having corresponding weighting vector $W = [w_1, w_2, \dots, w_n]^T$, where $\sum_{j=1}^n w_j = 1$ and $w_j \in [0, 1]$ is defined as,

$$WA(a_1, a_2, \dots, a_n) = \sum_{j=1}^n w_j a_j, \quad (1)$$

where $a_j \in R$ represents the argument variable.

2.3. ORDERED WEIGHTED AVERAGE(OWA) AGGREGATION OPERATOR

OWA (Ordered Weighted Averaging) operators are a family of aggregation operators commonly used in decision-making and data analysis (Yager, 1993).

An OWA operator of dimension n is a mapping $OWA: R^n \rightarrow R$ defined by an associated weighting vector w of dimension n , such that $\sum_{j=1}^n w_j = 1$ where $w_j \in [0, 1]$ in accordance with the formula that follows:

$$OWA(a_1, a_2, \dots, a_n) = \sum_{j=1}^n w_j b_j, \quad (2)$$

where b_j is the j^{th} largest element in the collection $a_1, a_2, \dots, a_n$.

The OWA (Ordered Weighted Averaging) operators exhibit multiple properties, including monotonicity, homogeneity,

idempotence, boundedness, and commutativity. Several authors have extended their work with OWA operators in different directions (Blanco-Mesa et al., 2019; Merigó et al., 2017; Rathod et al., 2025). We'll examine a numerical illustration to better understand how OWA operators function in practice.

Example 1: Assume F is an OWA operator of dimension four with weighting vector such that $w_1 = 0.3, w_2 = 0.1, w_3 = 0.2$ and $w_4 = 0.4$. If we desire to evaluate $F(0.4, 1, 0.8, 0.7)$ then we assign

$b_1 = 1, b_2 = 0.8, b_3 = 0.7$ and $b_4 = 0.4$. So, we calculate

$$F(0.4, 1, 0.8, 0.7) = (0.3)(1) + (0.1)(0.8) + (0.2)(0.7) + (0.4)(0.4) = 0.68.$$

OWA are symmetric aggregation functions that allocate weights according to the input value.

Special cases of the OWA operator, depending on the weighting vector w include:

1. Arithmetic mean where all the weights are equal, i.e. all $w_i = \frac{1}{n}$
2. Maximum function for $w = (1, 0, \dots, 0)$;
3. Minimum function for $w = (0, 0, \dots, 1)$;
4. Median function for $w_i = 0$ for all $i \neq k, w_k = 1$ if $n = 2k + 1$ is odd, and $w_i = 0$ for all $i \neq k, k + 1, w_k = w_{k+1} = 0.5$ if $n = 2k$ is even;

In financial contexts, aggregation operators serve as the mathematical backbone for portfolio selection methodologies, following the pioneering work of Markowitz (Markowitz, 1952) on portfolio theory but extending beyond single-criterion optimization. In the third section, stock selection analysis evaluates six companies in the retail and consumer goods sector using multiple criteria including expected returns, risk factors, liquidity, volatility, market trend fit, and ESG scores. The objective is to select the most reliable investment opportunities using Weighted Average (WA) and Ordered Weighted Average (OWA) methodologies to balance potential rewards against associated risks.

3. CASE STUDY: STOCK SELECTION FROM RETAIL AND CONSUMER SECTOR

The methodology adopted in this study utilizes advanced aggregation operators like WA and OWA operators to synthesize these diverse evaluation criteria into unified preference rankings. We understand this by the following steps as follows:

1. The stock selection process is from the standard data which are available on the website of Zerodha trading application. We construct a multicriteria decision matrix considering stocks name as an alternative and the purchasing parameters as a criterion which is shown in Table 1. Also, it should be noted that we keep current price column just for all stocks references purpose, it will not cover in calculation.

Table 1. Stock Selection Analysis: Retail and Consumer Sector

Criteria Stocks	Current Price (₹)	Expected Return (%)	Risk (0-10)	Liquidity (0-10)	Volatility (0-10)	Market Trend Fit (0-10)	ESG Score (0-100)
RAYMOND	192.45	16.5	6	6	7	7	68
VMART	174.35	18.2	7	5	8	7	66
RELAXO	186.75	14.5	5	6	6	7	72
BATAINDIA	168.9	13.2	4	7	5	6	75
JUBLFOOD	162.45	18.4	6	7	7	7	70
ARVIND	145.75	15.8	6	6	7	6	65

2. In Table 1 we can see there are some positive as well as negative criteria. Positive criteria which are higher is better are expected return, liquidity, market trend fit, ESG score. Negative criteria which are lower is better are risk, volatility. Accordingly, we have to normalize the data table which shown in Table 2. We use following formula to normalize the data.

- For positive criteria: Normalized value = $\frac{Value - Min}{Max - Min}$
- For negative criteria: Normalized value = $\frac{Max - Value}{Max - Min}$

Table 2. Normalized Data

Criteria Stocks	Expected Return (%)	Risk (0-1)	Liquidity (0-1)	Volatility (0-1)	Market Trend Fit (0-1)	ESG Score (0-1)
RAYMOND	0.66	0.33	0.50	0.33	1.00	0.30
VMART	1.00	0.00	0.00	0.00	1.00	0.10
RELAXO	0.26	0.67	0.50	0.67	1.00	0.70
BATAINDIA	0.00	1.00	1.00	1.00	0.00	1.00
JUBLFOOD	0.86	0.33	1.00	0.33	1.00	0.50
ARVIND	0.52	0.33	0.50	0.33	0.00	0.00

3. At first, we apply weighted average using balanced approach giving slightly higher weights to expected return and risk as they are typically primary consideration for investors. So, the weighting vector will be $W = \{0.30, 0.20, 0.15, 0.15, 0.10, 0.10\}$ and final weighted average score is given in Table 3.

Table 3. Stock's WA Scores

Stocks	WA Scores	Rank
RAYMOND	0.6465	3
VMART	0.7100	1
RELAXO	0.5170	4
BATAINDIA	0.3500	6
JUBLFOOD	0.7065	2
ARVIND	0.4800	5

4. Now we define OWA weights using optimistic approach as follows:

$$W = \{0.30, 0.25, 0.20, 0.15, 0.07, 0.03\}$$

To apply OWA weights first we reordered all criterion values as largest to lowest. So, the final score of each stock is shown in Table 4:

Table 4. Stock's OWA Scores

Stocks	OWA Score	Rank
RAYMOND	0.6469	4
VMART	0.5700	5
RELAXO	0.7513	2
BATAINDIA	0.7500	3
JUBLFOOD	0.8307	1
ARVIND	0.3955	6

3.1. COMPARATIVE ANALYSIS OF WA AND OWA OPERATORS

Key differences in the both methodologies are discussed as follows:

1. Weighted Average (WA):

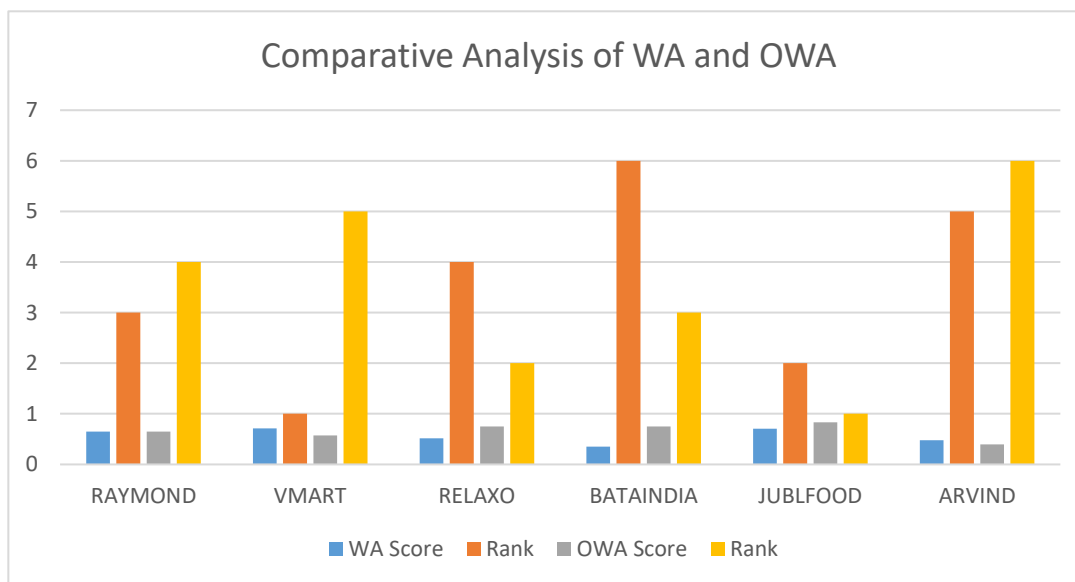
- Assigns specific weights to each criterion
- The same criterion (e.g., Expected Return) is always weighted the same for all stocks
- Focuses on the importance of specific criteria

2. Ordered Weighted Average (OWA):

- Sorts all criteria values from highest to lowest before applying weights
- Weights are assigned based on the relative position after sorting, not the criterion itself
- Focuses on the magnitude of values regardless of which criteria they represent.

VMART and JUBLFOOD exemplify contrasting investment models that emerge from different evaluation methodologies, with VMART representing the specialized high-return, low-risk investment that excels under traditional Weighted Average analysis despite having significant weaknesses in certain criteria, while JUBLFOOD represents the well-rounded performer that achieves prominence under Ordered Weighted Average assessment due to its consistently strong performance across multiple. Here in Figure 1, we show the comparative analysis of both the operators.

Figure 1. Comparative Analysis of Operators



The top stocks differ due to how Weighted Average (WA) and Ordered Weighted Average (OWA) methods prioritize criteria. VMART ranks highest under WA because it has a perfect expected return (1.00) and zero risk (0.00), which together contribute 50% of the total WA weight, while its poor liquidity (0.00) has minimal impact due to liquidity's lower weight (15%). In contrast, JUBLFOOD emerges as the top stock in OWA because it has consistently high scores across multiple criteria. Also, operator's practical implications are shown in Table 5 as follows:

Table 5: Practical Implications

When to prefer WA	When to prefer OWA	Investment Strategy Implications
When specific criteria matter more than others (e.g., you prioritize return over all else)	When you want to reward overall excellence	WA tends to favor specialists (stocks that excel in a few key areas)
When you want consistency in how criteria are evaluated	When you want to identify stocks with multiple strengths	OWA tends to favor balanced performers (stocks with multiple strengths)

When you want to minimize the impact of a single poor criterion	When the specific criterion doesn't matter as much as having strong values	
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4. CONCLUSION

This paper explores the application of aggregation operators in the context of stock selection for the Indian retail sector. By employing multi-criteria decision-making (MCDM) techniques, we evaluate six prominent Indian retail stocks: Raymond, V-Mart, Relaxo Footwear, Bata India, Jubilant FoodWorks, and Arvind. Each stock is assessed against seven critical parameters: current price, expected return, risk level, liquidity, volatility, market trend fit, and ESG score. This comprehensive framework enables a holistic evaluation of each investment opportunity, balancing financial performance with sustainability and market positioning considerations. The comparison between Weighted Aggregation (WA) and Ordered Weighted Aggregation (OWA) methods reveals significant shifts in stock rankings within the Indian retail sector. Under WA (with weights $W = [0.30, 0.20, 0.15, 0.15, 0.10, 0.10]$), VMART leads with a score of 0.7100, followed closely by JUBLFOOD at 0.7065, while BATAINDIA ranks lowest at 0.3500. However, when applying OWA, which reorders criterion values from largest to lowest, JUBLFOOD emerges as the top performer with a score of 0.8307, followed by RELAXO (0.7513) and BATAINDIA (0.7500), while VMART drops to fifth place with 0.5700. This striking transformation in rankings demonstrates how methodological choices in multi-criteria decision analysis can dramatically impact investment recommendations, highlighting the importance of selecting appropriate aggregation operators that align with specific investor preferences, risk profiles, and market perspectives when constructing retail sector portfolios.

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