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AHP-TOPSIS Weighting Method for Options Contracts

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1 Abstract

Searching for appropriate covered call contracts is often based on the seller's preconceived notions about what they should look for, done through filtering and guesswork, or otherwise decided through subjective methods. Using two multi-criteria decision-making tools, namely Analytical Hierarchy Process and TOPSIS, we created a combined method to weight and rank the available options contracts based on the user's individual preferences and needs. It should be noted that the general goal of a covered call is to generate income while maintaining an appropriate amount of risk for that client, so this method was written with that in mind. We found that this method provided clearer and more digestible results than the aforementioned status quo methodology. The process of deciding whether the results are objectively *better* is ongoing, but the benefit of removing guesswork should not be discredited.

2 Introduction & Problem Statement

When finding an options contract, a covered call in particular for this case, there are many interrelated variables and far too many alternatives to assess each one individually. A common solution is to use broad filters to remove contracts that do not suit the current purpose – e.g., one might have a particular expiration date and delta range in mind. Filters can narrow down the number of alternatives but still pose two problems: firstly, for a large stock with many contracts in the options chain, such as Apple, even heavy filtering returns many contracts to choose from. Secondly, and arguably more importantly, choosing the right filters can be an educated guess instead of a sure way to get the best contract for that particular instance. An advisor might choose a delta range of 0.2 to 0.4 because that is the default moderate range, but do they know what that really means and why they should or should not use that range? Often times the answer to both questions is no.

The problem we are aiming to solve is to elect the most appropriate contract for individual scenarios. The solution is twofold: individually rank each contract to give a clear winner, and use the desired *output* to drive the ranking, not filtering the input arbitrarily.

3 Solution

This project can be broken down into two distinct sections: 1. Using the Analytical Hierarchy Process (AHP) method to generate weights for each criterion, and 2. Using TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) to rank the alternatives based on those weights. AHP and TOPSIS are both multi-criteria decision-making systems (MCDMs) that rank the alternatives.

TOPSIS works by determining the “ideal” solution and ranking each alternative by its Euclidean distance from that solution. It does this by accepting criteria, alternatives, weights, and ideals. It first normalizes the matrix in order to compare differing units, then finds the overall distance to the ideal. TOPSIS generates the final ranking by their closeness score as compared to the ideal, not to each other. This means it is better suited for an often-changing set of alternatives, such as an options chain. Two drawbacks are: 1. TOPSIS does not help generate weights, the weights are determined and passed in by the user and 2. TOPSIS assumes each criterion is independent of the rest, which is not the case for options contracts – risk drives the yield, days to expiration drives the risk, etc.

AHP, on the other hand, works by creating a decision tree of criteria with respect to the main goal – shown in Figure 1 – then making pairwise comparisons about the importance of each criterion in order to generate global weights for each. Each alternative is then ranked by weighting each criterion in accordance to the pairwise matrix. This process works best for interrelated and/or qualitative criteria, and gives the final ranking by simple multiplication of weights. One drawback of this process is that the ranking is *comparative*, meaning a new alternative has the ability to change the ranking of everything, which is not ideal for a frequently changing, high volume set of alternatives like an options chain.

The reasoning behind combining these methods is multi-faceted. The criteria used to rank options contracts are inherently dependent, which goes against the TOPSIS assumption that each criterion is independent. That is why we used AHP to generate accurate weights of related criteria and transitioned to TOPSIS for the second half of this project. Using TOPSIS instead of AHP for the final ranking allows the frequent entry or changing of alternatives without changing the entire ranking. In addition, a dataset like this, although complicated, does not contain subjective data. Finally, the TOPSIS method of ranking is better suited for this case because a poor score in one criterion will drop the alternative to a low ranking when using AHP, but will not necessarily do that in the TOPSIS method, which is better suited for the case of selecting an options contract. For example a contract that is perfect in almost every criterion but has one anti-ideal can still be a top-ranked contract, even though it doesn't fit every ideal exactly.

TOPSIS allows for this contract to still be highly ranked by using Euclidean distance, which makes TOPSIS ranking with AHP weighting best suited for our needs.

4 Methodology

4.1 Criteria

To begin the weighting, we first needed to decide on criteria. We brought it down to the four main aspects that decide the profile of a contract: risk, yield, length of contract, and volume. Note that strike, among other eligible features, is not included – this is because while strike is a defining feature of a contract, strike simply indicates risk, which is already included. This also removes the prior judgment a user might have about what strike they think is best.

The criteria tree is shown in Figure 1 and each node will be explained in depth, but first there are two decisions the user must make, and a few hard boundaries that will be elaborated on later. The two decisions are as follows:

1. What is the ideal length of contract, in days?
2. Is it better to keep or to sell the underlying security?

Once those two questions are answered, the following hard boundaries are put in place to filter out contracts that fit any of the following criteria:

1. Contract volume 0 or 1
2. DTE (days to expiration) less than 7 days or greater than 2.5 times the ideal DTE
3. Probability in-the-money greater than or equal to 0.5

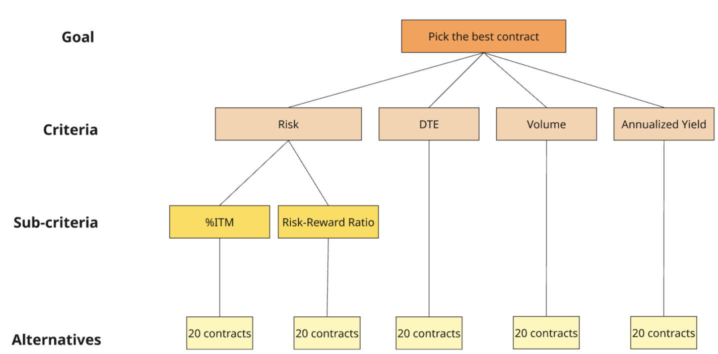

Figure 1: AHP Decision Tree

4.1.1 Risk

The risk node is broken down into two parts: the probability that the stock ends up in-the-money (stock price greater than strike price) by expiration, and the risk-reward ratio. The first is the probability factor, denoted as %ITM, for percent change of ending in-the-money, and is calculated using Black-Scholes, given in equations 1 through 4.

$$C = N(d_1)S - N(d_2)Ke^{-rt} \tag{1}$$

Where

$$d_1 = \frac{ln(\frac{S}{K}) + (r + \frac{\sigma^2}{2})t}{\sigma\sqrt{t}} \tag{2}$$

$$d_2 = d_1 - \sigma\sqrt{t} \tag{3}$$

The risk-neutral probability that an option expires in-the-money ($S > K$) is given as:

$$N(d_2) = \frac{ln(\frac{S}{K}) + (r - \frac{\sigma^2}{2})t}{\sigma\sqrt{t}} \tag{4}$$

where S is the spot price, K is the strike price, r represents the risk-free rate, σ the implied volatility of the option, and t the duration of the contract in years.

Equation 4 is our final equation to calculate the first child node of Risk. The hard boundary of excluding contracts with %ITM greater than 0.5 is because at 0.5, the odds of ending ITM are 50%, which indicates that the strike price is already equal to or less than the spot price. A strike price less than or equal to the spot is an in-the-money or at-the-money contract, which is not an advantageous contract to write in the scenario of a covered call.

The second child node of risk is the risk-reward ratio: this number tells us how much possible loss the contract takes on as a ratio to the possible benefit. How we calculate this depends on whether the user intends to keep or sell the underlying security.

For writing a covered call where the writer intends to keep the underlying security, the biggest risk financial risk comes in the scenario where the stock price exceeds the strike price and the writer must buy back the contract in order to avoid assignment. Assuming the user would buy back right when the price passes the strike, our risk factor is given as:

$$Risk = BTC - Mark \tag{5}$$

Where BTC indicates the estimated cost of buying to close the contract when the spot price is equal to the strike price, approximated using Black-Scholes and the implied volatility of that expiration's closest at-the-money contract. $Mark$ is the premium-per-share received, since that is kept by the seller regardless. The highest possible reward in this scenario occurs if the stock price remains the same, meaning the reward is simply equal to the mark. Therefore, the risk-reward ratio is:

$$RR_{keep} = \frac{(BTC - Mark)}{Mark} \tag{6}$$

In the case that the writer does want to sell their underlying asset, the largest financial risk is no longer that the stock price will increase to above the strike. In fact, the stock price increasing yields the highest gain since the writer will then receive payment in exchange for their shares along with the premium, giving the reward factor as

$$Reward = (S_i - K) + Mark \tag{7}$$

where S_i is the stock price at entry and K is the strike price. In this scenario, the largest financial risk happens if the stock price were to fall and the shares lose all value:

$$Risk = S_i - Mark \tag{8}$$

$$RR_{sell} = \frac{(S_i - Mark)}{(S_i - K + Mark)} \tag{9}$$

4.1.2 Days To Expiration

The next node is DTE, or days to expiration. The user already gave their ideal value for this, so each alternative has its adjusted DTE value computed as the absolute distance from the ideal.

$$DTE_{adj} = |DTE_{ideal} - (Date_{expiration} - Date_{current})| \tag{10}$$

Contracts with DTE less than 7 are removed from the pool because this tool is for advisors, not day traders, so those short contracts are already non-viable. The reasoning behind removing them altogether comes from their annualized yield – because their span is so short, it amplifies the annualized yield, causing them to score higher than they should. We removed contracts with a DTE more than 2.5x the ideal for the reasoning that they are also non-viable and skew the results by scoring very well in other areas.

4.1.3 Volume

The third node of the decision tree is volume – while it is not a highly important field for many advisors, being in the matrix at all provides a tie breaker and removes outlier prices. By excluding contracts with volumes of 0 or 1 from the pool, we removed one-off contracts with skewed prices that do not reflect the actual value or price the user would get for their contract. Even when ranked as an unimportant field, volume can serve as a tiebreaker by prioritizing contracts with higher volumes.

4.1.4 Annualized Yield

The final node is annualized yield: the premium earned from the contract if it were implemented repeatedly for one year. The reasoning behind using annualized yield instead of one-time yield is that simple yield disproportionately boosts very large DTE contracts because their single yield is higher, despite the fact that they tie up stocks for their long duration and are not easily repeatable, leading to worse long-term gain.

Annualized yield for a single contract is simply calculated as

$$Yield_{annual} = \frac{Mark \times 365}{S_i \times DTE} \tag{11}$$

with the hard boundary that the maximum number of times a contract will be repeated in a single year is once a month, or 12 times in a year. To reflect this lower bound, any contract with DTE less than 30 is treated in this calculation as if its DTE is equal to 30.

4.2 Weighting

After selecting our criteria, we created a comparison matrix. AHP uses pairwise comparisons, so the user is presented with a set of two criterion and must decide which is more important to the parent node and by how much. The value of intensity is the Saaty scale of 1 to 9, with 1 being equal importance and 9 being 9 times more important. The pairwise comparisons are listed in Table 1.

Criterion A	Criterion B	Goal
Risk	DTE	Best Contract
Risk	Volume	Best Contract
Risk	Annualized Yield	Best Contract
DTE	Volume	Best Contract
DTE	Annualized Yield	Best Contract
Volume	Annualized Yield	Best Contract
R-R Ratio	%ITM	Risk

Table 1: Each pairwise comparison with regard to its local goal

Once values are received from the user, the AHP software turns those values into global weights, or the weight of each criterion with respect to the total goal. In this case, the total goal is to select the best contract. This also means that the "Risk" node does not get its own global weight, but risk-reward ratio and %ITM get their global weights as subsets of the Risk calculated weight.

After computing the weights, the next step was to determine the ideal value of each criterion. For example, a lower risk-reward ratio indicates less risk per reward, so the ideal is 0 (minimize). For others, namely %ITM, the ideal depends on whether the user wants to keep or sell their underlying; a lower risk of ending in-the-money correlates to a lower risk of being assigned, which is

Criterion	Ideal Value
%ITM (Want to Keep)	0
%ITM (Want to Sell)	∞
R-R Ratio	0
DTE	0
Volume	∞
Annualized Yield	∞

Table 2: All of the criteria and their ideal values. %ITM is the only criterion that changes ideals depending on if the user wants to keep or wants to sell the underlying. Reminder that DTE is not raw days to expiration, but instead distance from the ideal value.

good if the user wants to keep their stock but bad if they want to sell. All of the criteria and their ideal values are listed in table 2.

4.3 TOPSIS Ranking

After calculating our weights and ideals, we were able to pass those values to our TOPSIS model for the final ranking. The first step was to determine the ideal length of the contract and whether the goal was to keep or sell. We then removed the non-viable contracts from the pool based on the hard boundaries outlined previously, and passed each viable alternative to the TOPSIS model with its metrics and their respective weights, along with the ideal value for each metric. The TOPSIS model then took this information and calculated the Euclidean distance to the ideal contract and returned the alternatives in ranked order.

5 Conclusion

Bearing in mind the problem statement of finding the best options contract for individual scenarios, the combined AHP-TOPSIS method shows improvement contrasted to the status-quo filter method. It consistently gave strong contracts at the top of the ranking, adapting as the weighting matrix was adjusted. The process of objectively comparing the performance of the options chosen this method to the ones of the filter method is ongoing and complex, but the definitive ranking and automatic removal of anti-ideal contracts for the goal should not be discounted.

An important caveat to mention is that the result of the ranking depends entirely on the user entering matrix values that truly represent their needs. It is a known phenomenon in behavioral economics that humans are often wrong when asked to judge their own risk tolerance, so next steps include finding ways to truly gauge what the user wants beyond what they state. This could include natural language processing, asking pointed questions instead of collecting numeric data from the user directly, or other methods used to remedy the misalignment of stated versus actual. In the meantime, having the user select from default profiles with preset weighted matrices instead of creating the matrices themselves can help mitigate human error.

There are many other ways to improve upon and fine-tune this method, such as adding in more criteria, using natural language processing, or taking into account the user's own predictions or sentiments. Even before further improvements are implemented, the method outlined in this paper appears to perform better than and improves upon the drawbacks of simple filtering.

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