Comparing the Awesome Oscillator to a Time-Based Trade: A Framework for Testing Stock Trading Algorithms

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INTRODUCTION

There has been a recent trend in equity trading that supports a belief that volume precedes price. Put another way, a stock's momentum is an indicator of its future trend. This supposition has lead to a variety of studies and approaches that expand and build on this theory. Bill Williams, Ph.D. has developed several models in addition to making a career and successful business exploiting these supposed market opportunities. One method created by Williams uses an oscillator to determine a stock's momentum. The output of the oscillator creates an indicator of a stock's momentum and subsequently a stock's future value. According to Williams, his algorithms and approaches are profitable even under volatile market conditions. Williams approach uses several "signals" to identify equity patterns. One of Williams' indicators is a simple oscillator. This oscillator was originally developed by Tom Josephs to try to track Elliot wave. Williams adopted and modified the algorithm and subsequently named it Williams Awesome Oscillator (AO). It is now included as part of his Profitunity trading course and software.

This paper describes a framework in which various equity trading algorithms can be tested. As an initial study, the AO algorithm was compared to a time-based trade as the basis for testing the framework. The framework is designed to be fully automated and capable of not only testing algorithms, but employing them and building a method for profitable stock trading. As part of the testing, the framework was used to evaluate whether the AO would perform better than a simple time-based trade. In this context the framework used the time-based trade as the control or "untreated" sample and the AO algorithm as the treatment sample.

The framework employs an intelligent agent to retrieve high volume stocks as defined by a selected source and used these stocks as the basis for both algorithm evaluations. In addition to the stock trading pool, the framework takes into account number of trades made, money management, commissions, and stop-loss transactions. To evaluate the framework, these variables were controlled to test a specific hypothesis: would Williams' Awesome Oscillator algorithm yield a greater return on investment compared to a simple time-based buy/sell algorithm when trading high-volume stocks. Stock price data was collected after the market closed and then used to simulate actual trades during the day. The framework is a fully automated system to gather and store the data for processing. Using this framework the AO algorithm was compared to a time-based stock trading algorithm over a period of five days and 52 stocks.

BACKGROUND AND OTHER RESEARCH

Williams' Awesome Oscillator (AO) algorithm is based on the work of Tom Joseph. Tom Joseph developed an oscillating algorithm that was based on R. N. Elliot's work in predicting the stock market's direction. Elliott believed markets had well-defined waves that could be used to predict market direction. In 1939, Elliott detailed the Elliott Wave Theory, which states that stock prices are governed by cycles founded upon the Fibonacci series.[1] In 1981 Tom Joseph developed an oscillator that pulls back to the zero baseline at least 94 percent of the time during profit-taking. The oscillator is seen as successful because it lets a trader stand aside until the profit-taking is over. When the Elliott Oscillator pulls back to zero, it provides a highly accurate area where it can predict that profit-taking is actually over, and the trend is ready to resume.[2] Williams combined Josephs' oscillator with other indicators to create a comprehensive trading package.

The field is crowded with significant research in the area of predicting the stock market and identifying trends. Much of this research has been converted into commercial stock trading algorithms or commercial trading courses. Recent research has included examining adaptive rule based trading, volume analysis, and the applications of intelligent agents in market simulations. The framework used in this paper's research employs many similar approaches and methods.

On Balance Volume (OBV) was developed by Joseph Granville and introduced in 1963 to the technical community inside the pages of his book, *Granville's New Key to Stock Market Profits*. On Balance Volume is a momentum indicator that measures positive and negative volume flow. Colby and Meyers, not to mention numerous other analysts, put OBV through additional summations, smoothings and measures of momenta without finding any advantage over simple moving averages. [3]

FIGURE 1
AN EXAMPLE OF OBV BENEFITS[3]

Abhishek Mistry published a paper in 2003 describing a simulation framework that employed intelligent agents as entities in a market, such as traders, market makers, and research analysts. The goal of Mistry's research was to develop a market simulation framework that could be employed by economists to simulate market activity.[4] Mistry's work culminated with a market simulator that attempted to match the stock market environment through non-rational and so called noise trading. Unlike the framework developed here Mistry's work is designed to simulate market chaos and not test a specific approach or algorithm.

Markus Bengtsson and Magnus Ekman developed a test for adaptive rule-based stock trading. The objective of their research was to create a rule-based trading framework and test the Efficient Market Hypothesis.[5] Bengtsson and Ekman's work employed adaptive rules to test the Efficient Market Hypothesis (EMH). EMH states that at any given time, stock prices fully reflect all available information. EMH is based on the argument that in an active market that includes many well-informed and intelligent investors, stocks will be appropriately priced and purchased. If a market is efficient, no information or analysis can be expected to result in out performance of an appropriate benchmark. Intuitively this assumption seems flawed as there are many "well-informed" investors who trade in the market. Bengtsson and Ekman sought to use adaptive rules to test this theory. Unlike Bengtsson and Ekman's research the framework discussed in this paper assumes the market will behave in its typical entropic and seemingly unpredictable manner.

There has been quite a bit of work in developing and studying algorithms and methods for predicting the market. This background is not exhaustive, but much of the prior research emphasizes the development of algorithms or simulating the market environment, as compared to developing a framework for isolating and testing multiple algorithms. This paper will discuss two main objectives. The first objective is to develop a framework for testing trading algorithms. The second objective is to determine whether the AO will perform better than a time-based algorithm. It should also be noted here that the AO algorithm is only one of many oscillator algorithms that have been developed to indicate stock trends.

METHODOLOGY

It is helpful to get a basic understanding of trading terms to aid in the discussion of the research methodology. Traders may elect to buy long or sell short. The terms buy and sell do not necessarily represent entering and exiting a position. For example, a trader may "buy long" or "sell short." Both of these actions enter a position. Selling short is the opposite of buying long. That is, short sellers make money if the stock goes down in price, where long buyers make money if the price goes up. In these cases to exit the position the trader would "sell" stock bought long and "buy" stock sold short. In this context, a round-trip trade would consist of entering and exiting a position.

Traders may opt to put a "safety net" underneath their transactions. This net is called a stop-loss. A stop-loss is designed to limit a trader's loss on a security position. Stop-losses are typically placed in terms of a percentage, limiting the loss to a percentage of the investment.

The prices of stocks are measured in terms of bars. A bar is a measurement of price/time and consists of a high, low, open, and close price. Bars are relevant to the resolution of pricing data that is typically used for analysis. The framework utilizes bars of historical data to simulate actual trades.

SAMPLING DESIGN

Each day Investors Business Daily (IBD) posts high volume stocks for a given period. The framework used an intelligent agent to fetch IBD's list of high-volume stocks every morning at 10:00am. IBD posts five upward trending stocks (increasing in price) and five downward trending stocks. The selection of samples from IBD was chosen because it provided securities that have been "pre-identified" as volume movers, minimizing the impact of the uncontrolled variables. The agent was instructed to download and parse the data off the market open time of 9:00am to eliminate market manipulations from the previous day. Data was collected for 1-2 days every other week for a total of 5 days. This sampling method was done to get a broader range of samples over time, increasing the exposure to the uncontrolled variable of economic conditions.

CONTROLLED VARIABLES	DESCRIPTION
Number of trades per day	Defined how many round trip trades the algorithm could execute
Stop-Loss percentage	Defined the percentage of stop-loss
Market entry and exit	Controlled the time period when trades could be made
Amount of money for trade	Defined the amount of money allowed for each trade
Money Management	Selected the money management technique to be applied
Commissions	Defined the commission that would be applied to enter/exits
Oscillator bar length	Defined the time-price interval for oscillator calculations

UNCONTROLLED VARIABLES	DESCRIPTION
Market prices	This variable is set by the market (supply and demand) – the effect of this variable is minimized by using high volume stocks
Market timing	This variable is related to market manipulations – the effect of this variable is minimized by trading in the center of the day 10am – 3pm
Economic conditions	This variable is defined by the happenings in the world – the effect of this variable is minimized by using high volume stocks

TABLE 1. CONTROLLED & UNCONTROLLED VARIABLES

RESEARCH DESIGN

A framework was created to automatically collect, evaluate, and store stocks and algorithms. A detailed data model can be found in appendix A. 1300 lines of code were written using PHP to create an intelligent agent, a data importer, the AO and time-based algorithms, and run profile management.

Inside the run profile component of the framework, each controllable variable was implemented as part of the run definition. The effects of uncontrolled variables were minimized using the sample selection and trading times.

The framework automatically downloads IBD data and ticker bars on a scheduled basis. The bar and IBD data are stored, so that the algorithms can be tested. This data is used in conjunction with the run variables to simulate trades throughout a trading day.

The framework was designed to conduct the following basic operations to test the AO versus the time-based algorithms:

1. Use high volume stocks as identified by Investors Business Daily (IBD) as selected trading pool
2. Make a single trade on these stocks (buy long or sell short). X “round-trip” trades per day
3. Use the AO algorithm and a time-based trade as “what” transaction to make “when”
4. Each trade will be conducted for each alternative: AO and the time-based algorithm
5. Allocate a pool of money to each algorithm and allow the algorithm to go into debt
6. Use the same amount of money per trade for each algorithm

Algorithm performance data from each run across all stocks is collected and stored as part of the framework’s operation. Run variables can be manipulated for each processing run by adding another runvariable record to the framework database. Details of the calculations used to determine the AO algorithm indicator can be found in Appendix A.

RUN VARIABLES	
Runvarid	Identifier for the run variable record
Symbol	Stock symbol
Bardate	Date of the IBD data for this stock
Tradenum	Trade sequence number (for multiple roundtrip trades)
Traderevenue	Dollar outcome for the run record
Enterprice/ Exitprice	Price paid at entry/exit
Tradedate	Position exit date
Tradetime	Position exit time
Numshares	Number of shares in the transaction
Pricedirection	Direction of price moving up or down

TABLE 2. COLLECTED RUN DATA

<u>EXAMPLE TIME-BASED RUN</u>

1. Make entry (long or short) at 10:00am
   a. Only take long position for stocks that are positive (price moving up)
   b. Only take short position on stocks that are negative (price moving down)
2. If stop loss percentage is reached at any point during the day then position is exited at market rate, at that time
3. If position is still held at 3:00pm, exit

<u>EXAMPLE TIME-BASED RUN</u>

1. No trades made until after Oscillator Algorithm generates signal to make transaction
   a. Only take long positions for stocks that are positive (price moving up)
   b. Only take short positions on stocks that are negative (price moving down)
2. Use AO signal to enter and exit trades – use 1 minute bars
3. If stop loss percentage is reached at any point during the day then position is exited, at market rate, at that time
4. If position is still held at 3:00pm, exit

The time-based algorithm is considered the control and the AO algorithm can be viewed as the treated samples. For both of the AO and time-based algorithms, runs were made with the trading day limited between 10:00am and 3:00pm. No (0%) commission was applied, with a 5% stop loss. Each trade was limited to $1,000.00 with 1 round-trip trade per day. Symbol, bardate, and pricedirection are all set by the high volume IBD trading pool. The data elements collected from a run can be seen in Table 2.

DATA ANALYSIS

The results of the run were summarized using Microsoft Access. Basic descriptive statistics were used to determine which algorithm performed better. Additional analysis was conducted using Mathematica and SPSS to examine the resulting distributions and apply paired t-tests to do hypothesis testing.

The analysis of the framework was done by evaluating how well it isolated and controlled the testing variables. The data from the processing runs was used to evaluate whether the framework was successful in doing so. If the framework was successful, the data from both samples should be from similar distributions and as a result have similar characteristics exclusive of how the stock performed. A .025 level of significance (97.5% confidence interval) will be used to determine the validity of the framework and measures of the differences between the two algorithms. This will increase the type II error in this experiment. However the type II error can be reduced in the future as additional samples are gathered, using the validated framework.

LIMITATIONS

The use of judgment sampling may have affected the outcome of the algorithm assessment. This is because the sample was heavily dependent on a single source of what was effectively secondary data. The current collection methods of data used for processing will not facilitate real time trading. Additionally, the timing of the sample collection may introduce or increase errors caused by some of the uncontrolled variables such as economic conditions.

FINDINGS

Fifty-two stocks were tested using each algorithm over the course of 5 non-consecutive days. Table 3 displays the descriptive statistics for each distribution's revenue. Further analysis using a paired t-test shows that there is a low correlation and a significant difference between the two samples.

Descriptive Statistics

	N	Range	Minimum	Maximum	Sum	Mean	Std.	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
AORev	52	54.81	-40.00	14.81	-36.25	-.6971	8.84129	78.168	-1.952	.330	7.029	.650
TimeRev	52	377.690	-129.150	248.540	12.244	.23546	67.349158	4535.909	2.413	.330	7.442	.650
Valid N (listwise)	52											

Paired Samples Correlations

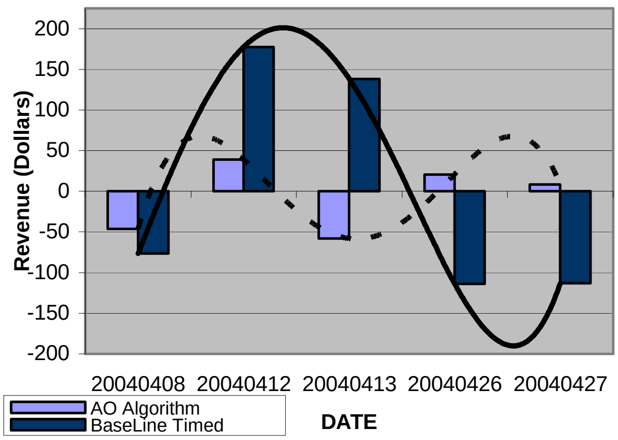
		N	Correlation	Sig.
Pair 1	AORev & TimeRev	52	.281	.044

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					97.5% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	AORev - TimeRev	-.932562	65.419584	9.072064	-21.8846	20.019476	-.103	51	.919

TABLE 3. STATISTICS FOR TOTAL REVENUE & PAIRED T-TEST

The timed algorithm had larger yields and losses as compared to the AO. This is shown in Figure 2 on the following page, where the run revenue is summarized for each trading day, by run algorithm. The chart in Figure 2 shows revenue per day. The bar data have been fit with a 4^{th} order polynomial trend lines to



Date	AO	Timed
20040408	-46.33	-76.53
20040412	38.93	177.43
20040413	-58.14	138.25
20040426	20.73	-113.80
20040427	8.55	-113.10
TOTAL	**-36.25**	**12.24**

FIGURE 2. DAILY TRADE REVENUE

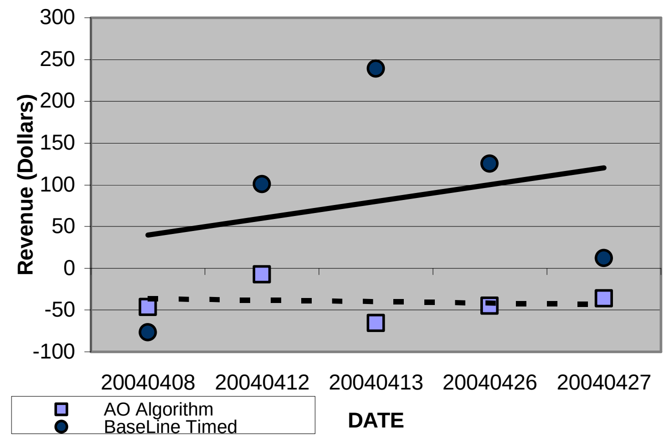


FIGURE 3. REVENUE TREND

exaggerate the pattern. Lower order polynomial trend lines give a consistent, yet less dramatic pattern. Histograms of each sample's revenue show that the mean revenue for both distributions is effectively zero. The daily trade revenue indicates the total performance of each algorithm when run against that day's high volume trading pool. Figure 3 shows accrued revenue over time with linear trending lines. This chart indicates the overall trending of the samples taken during these runs.

To evaluate the performance of the framework, a t-test was used to examine whether the framework kept variables constant between the two algorithm samples. The results of comparing the investment amount between the two samples are below in Table 4.

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	AOInvest	984.67577	52	14.759581	2.046786
	TimeInvest	986.05240	52	15.079120	2.091098

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	AOInvest & TimeInvest	52	.959	.000

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	97.5% Confidence Interval of the Difference Lower	Upper			
Pair 1	AOInvest - TimeInvest	-1.376635	4.282123	.593824	-2.748077	-.005192	-2.318	51	.024

TABLE 4. INVESTMENT AMOUNT PAIRED T-TEST

Investment amount is one of the controlled variables, but it would be expected to have some variation because the actual amount of investment would depend on the price of the stock, at position-entry time. Because shares cannot be purchased in fractions, the framework would have to adjust the investment amount to fit the price without exceeding the run amount of $1,000.00. The statistical data shows a high degree of correlation, with a significance that is within the confidence interval. These results accept the null hypothesis that there is no difference between the two samples.

CONCLUSIONS

In this paper a trading algorithm test framework is proposed and investigated. The framework can be evaluated by examining whether it was able to control trading variables and provide a platform for the evaluation of algorithms' performance. In summary, the contributions of this research can be divided into two main parts. The first part is a proposal of a framework that could be used to effectively isolate and test trading algorithms controlling the trader's variables while minimizing the impact of external variables such as market prices and economic conditions. The second part is the evaluation of the AO trading algorithm.

The framework had two objectives: to automatically collect appropriate data for analysis and store this data for processing and secondly, to control the variables used for testing. The framework consistently demonstrated an ability to collect and store the data necessary for processing the stock using the two defined algorithms. The qualification of this measure is purely empirical. However, if this were not the case it would not have been possible to perform the experiment.

How well the framework controlled the variables was measured across several variables, with two variables not being tested; stop-loss and commission. In the case of investment amount, the t-test confirmed the null hypothesis that there is statistically no difference between the two samples; reinforcing the position that the framework did control this variable. Additionally, the enter and exit trade-times for the time-based algorithm was held constant with no variance.

It is not surprising that the AO algorithm did not perform as well the time-based algorithm. The time based algorithm was able to take advantage of volume momentum while the AO algorithm was subject to price fluctuations during the day. On some days the AO outperformed the time-based algorithm and on others it did not. Despite this, the data trends and statistical tests confirm that there is a difference between the two samples and that the time algorithm performed better than the oscillating algorithm. While the results appear to indicate better performance from the time algorithm, additional data/runs are necessary to make a definitive conclusion.

The time-based algorithm had higher yields compared to the AO. This may be caused by the fact that the tests used volume trending stocks and the oscillating algorithm was not allowed to oscillate, therefore losing any potential performance advantage.

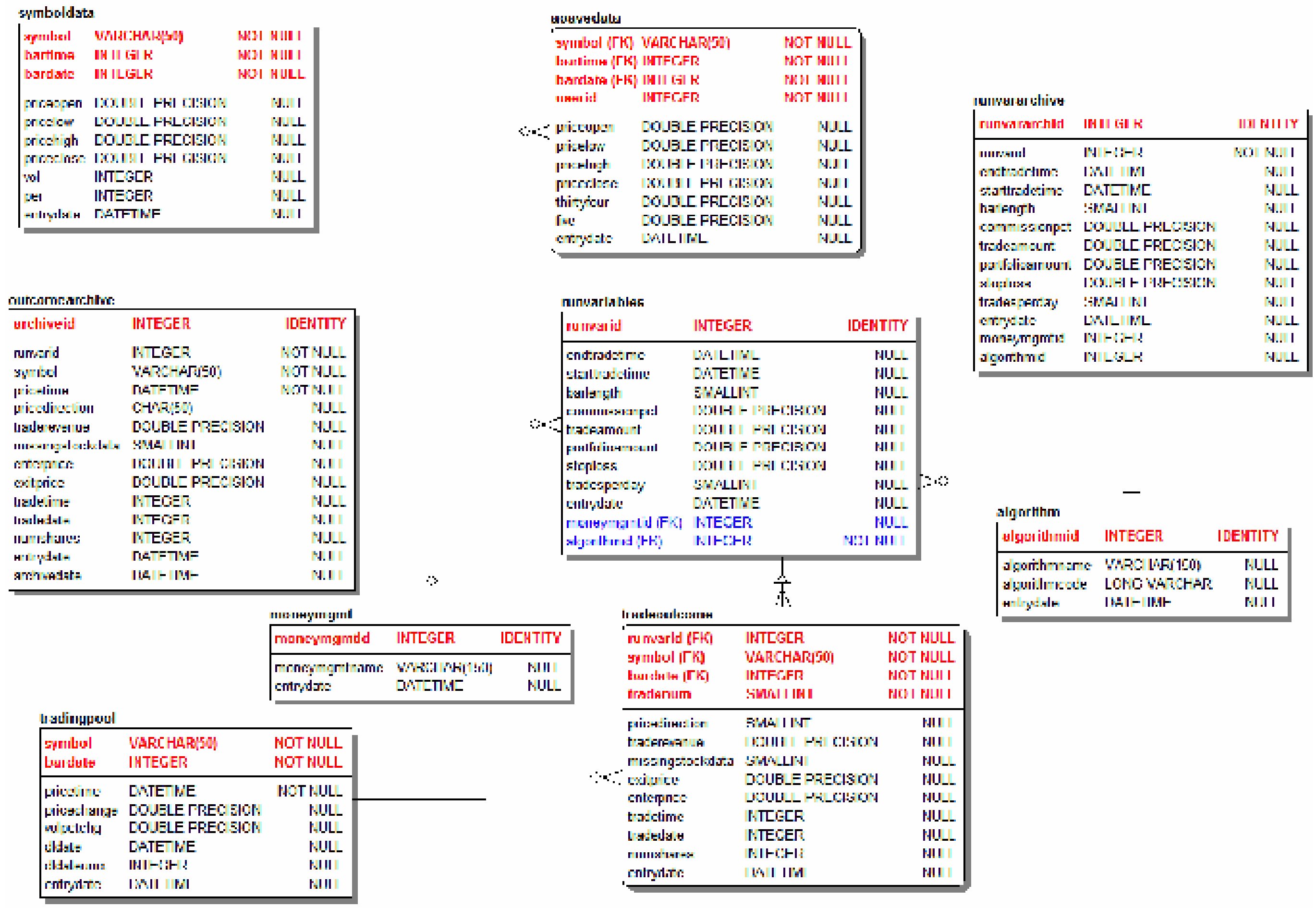
FUTURE WORK

The AO is designed to actually oscillate. In the current research the oscillation was limited to only a single trade per day. Ideally the oscillator would execute several trades per day depending on the momentum, therefore avoiding negative trends and purchasing repeatedly on profitable trends. The current framework could be used to test the AO with multiple trades per day. Additional data analysis could be conducted to examine the differences between upward and downward volume stocks, and the effects of different bar lengths as well testing other algorithms.

In the context of testing other algorithms within the framework, analysis of other variables such as the impact of commissions or money management is necessary to further validate the testing framework. Another area where additional investigation may be appropriate, is examining the impact of the selected sample from IBD. The use of, or comparison to, other high volume stocks would conclusively determine the validity of the framework.

APPENDIX A

FRAMEWORK DATA MODEL



WILLIAMS AWESOME OSCILLATOR

AO makes trades based on market momentum

- The basis for this is that stock in motion tend to stay in motion, in the direction that they are going
- Conceptually momentum indicates the price trend

A Bar contains open close high and low for a given period (1 minute to one day)

- 5-bar moving average of midpoints subtracted from 34-bar moving average of midpoints = market momentum
- Midpoints are defined by $\frac{H-L}{2}$ where H ≡ high of period (bar) and L ≡ low of period (bar)

General Oscillator: n period simple moving average is: $\frac{\sum_{i=1}^{n} P_{t-i+1}}{n} = Average(n,t)$

Where n is the number of periods, P is price at time (t)

AO = Average (5,t) – Average (34,t)

- If AO is positive and momentum is positive enter or hold, if momentum is negative exit or hold
- If AO is negative and momentum is negative enter or hold, if momentum is positive exit or hold
- If AO is 0 hold

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