MSDS 451 Term Project Checkpoint A
Project Report: Adaptive Global Income and Growth (AGIG) ETF

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1. Introduction

This research project proposes the development of a robust, adaptive investment framework, the Adaptive Global Income and Growth (AGIG) ETF, designed to manage portfolios dynamically over time, moving beyond simple, single-period decisions (Markowitz, 1952). The fundamental concept is to make cutting-edge quantitative research—typically reserved for large hedge funds—available to all personal investors in a low-cost ETF structure. The starting point of this research is the Modern Portfolio Theory (MPT), pioneered by Markowitz (1952), which established the principle of maximizing return for a given level of risk. However, MPT will need to be extended to adjust to changing market conditions and times.

The AGIG ETF overcomes these limitations by integrating Artificial Intelligence (AI) and Operations Research (OR). The fund's objective is to provide personalized financial planning for all age groups, optimizing for high Growth for younger investors and controlled Income (consistent withdrawals, e.g., the 4% rule) for retirees, via dynamic risk control.

2. Literature Review

The AGIG ETF strategy will augment the MPT by using machine learning and artificial intelligence methods.

2.1 The Need for Better Risk Control

The original idea established the core trade-off: more risk, more potential reward (Markowitz, 1952).

- Conditional Value at Risk (CVaR) - CVaR will be the primary risk measure. CVaR is much better than older methods because it measures the size of the actual expected loss during the worst market downturns, protecting investors from "tail risk" (Chen 2025).

2.2 Dynamic Portfolio Management with AI and OR

To move from a static strategy to one that adapts daily, especially to handle assets with "fat tails", the ETF shall use two key computational techniques:

- Solving the Two-Goal Problem (OR): The fund has two conflicting goals: maximize growth and minimize CVaR risk. The proposal is to solve the "Multi-Objective Problem" using an intelligent optimization algorithm called NSGA II (Kaucic, Moradi, and Mirzazadeh, 2019). This tool from Operations Research finds the perfect balance of investments to meet both Growth and Income targets.
- Achieving Long-Term Stability (AI): The ETF will use Reinforcement Learning (RL), specifically the Actor Critic algorithm, to manage the portfolio minute by minute. This technique is like a self-teaching game where the system learns the best long-term moves. Crucially, we use Performance-Based Regularization (PBR) to stabilize the input data, stopping the AI from making wild, erratic changes that ruined older models (Ban, El Karoui, & Lim, 2018).

- Experiments have been conducted using Financial Transformer Reinforcement Learning (FTRL) for Portfolio Management to uncover latent linkages between assets. FTRL outperformed other RL learning methods in determining returns, Sharpe Ratio, and Sortino ratio, and achieved greater than 40% higher average cumulative returns (Ren et al. 2025).

3. Methods

The AGIG ETF adopts a quantitative, algorithmic, and data-driven approach designed for automated implementation.

3.1. Asset Allocation and Diversification

The fund aims for a diversified portfolio encompassing US and foreign stocks, mutual funds, commodity ETFs (Gold, Silver), Bitcoin, US Treasuries, and Real Estate ETFs. This explicit leverage of the diversification principle is often noted as the "closest thing in investment to a free lunch", a quote attributed to Markowitz.

- Real Estate Integration: Real estate is incorporated through REIT-based ETFs, providing the necessary liquidity for this alternative asset class. Real estate serves as a crucial diversifier, historically showing extremely low correlations with traditional equity assets, thus offering strong risk-reduction benefits. The downside is that there are some tax-related considerations with REITs; however, they tend to provide recession-proof investments in the portfolio (Waterworth 2025).
- Strategy Reconciliation: The fund proposes a combination of the desired buy-and-hold/SIP structure by implementing a Strategic Asset Allocation (SAA) for long-term targets, augmented by Tactical Asset Allocation (TAA) driven by AI/ML for dynamic risk mitigation and periodic rebalancing as proposed by Sharpe et. al in Managing Investment Portfolio: Asset Allocation.

3.2. Analysis Methods (Forecasting and Risk Modeling)

The methodology consists of two critical sub-domains -

1. Forecasting: The primary forecasting tool is the MBi-LSTM network for predicting asset prices, returns, and risks. Its superior accuracy (often exhibiting the lowest MAE and RMSE) over traditional models makes it ideal for generating the critical input parameters (expected return vector and covariance matrix) required for optimization (Gaurav, Baishnab, and Singh, 2025)..
2. Risk Modeling: The ETF fund shall prioritize measures reflecting downside risk and non-normality. As described earlier, CVaR will be calculated, as it addresses the issues inherent in mean-variance analysis, particularly concerning tail risk.
3. Estimation Error Mitigation: To stabilize input parameters, notably the covariance matrix, the ETF will employ techniques such as Performance-Based Regularization (PBR). This approach is designed to protect against estimation errors in the portfolio variance, thereby improving out-of-sample performance (Ban, El Karoui, & Lim, 2018).

3.3. Decision-Making (Buying/Selling/Rebalancing via AI)

A multi-period, dynamic control approach governs investment decisions.

1. Multi-Objective Optimization: The core problem is formalized as minimizing downside risk (CVaR) while maximizing expected returns (or Net Present Value/NPV). This non-trivial trade-off is solved using the meta-heuristic NSGA-II to find the set of Pareto-optimal weights that balance the conflicting objectives. The output is the target asset allocation vector.
2. Dynamic Rebalancing (Optimal Control): The rebalancing policy is defined as an optimal control problem. We deploy the Actor-Critic Reinforcement Learning (RL) algorithm for dynamic rebalancing. The RL agent's reward function will be explicitly tied to maximizing long-term wealth, while adhering to the fund's investment philosophy (Growth and Income) and dynamically managing cash flows related to investor contributions (SIP) and redemptions (4% withdrawal rule). This enables the system to adaptively adjust compositions in response to evolving market conditions (Ban, El Karoui, & Lim, 2018).

4. Results

The research on integrating advanced quantitative techniques provides strong evidence supporting the AGIG ETF's methodological approach.

4.1 Superior Predictive Performance using Deep Learning: Research consistently demonstrates that deep learning models provide high predictive accuracy. Specifically, models like MBi-LSTM exhibit the lowest error terms (MAE, RMSE) when forecasting stock returns, outperforming statistical methods like ARIMA, SVR, and sophisticated ensemble models.

4.2 Enhanced Optimization Efficiency: Using multi-objective optimization techniques like NSGA has proven highly effective. Studies comparing NSGA-enabled portfolio methods to the Mean-Variance Markowitz (MVM) model show significantly higher similarity to actual returns (Ban, El Karoui, and Lim, 2018). These multi-objective models consistently achieve high portfolio returns with risk levels comparable to, or better than, conventional strategies.

4.3 Benchmarking and Backtesting: The portfolio will be benchmarked against S&P 500 index to measure performance and also backtested with as much data available as possible. The proposal to use MBi-LSTM networks will require a large amount of data for training and testing the model.

5. Conclusion

The Adaptive Global Income and Growth (AGIG) ETF is uniquely positioned to address the needs of the modern investor by merging robust portfolio theory with cutting-edge AI/ML and Operations Research methodologies. The fund successfully leverages the "free lunch" of diversification by incorporating low-correlation assets like Real Estate ETFs and employs dynamic AI to manage risk and cash flows associated with the SIP and 4% withdrawal goals.

The shift from static MPT to a multi-period optimal risk control framework (utilizing MBi-LSTM for forecasting and NSGA-II/RL or FTRL for optimization) provides the essential algorithmic foundation for a sophisticated, modern investment vehicle.

Concerns and Next Steps

The primary challenges moving forward are rooted in the computational complexity and theoretical rigor of the methodology:

1. Lack of expertise: With a limited Finance background, this will be an experimental approach.
2. Complexity: Given the time constraints, the complexity is too high with the implementation of various modules.

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