GOD MODE: The Theoretical Upper Bound of ETF Trading

A Benchmark of Perfect Foresight Performance
or, how much is the light speed in your trading environment?

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Abstract

This report documents the "God Mode" strategy, a theoretical benchmark designed to determine the maximum possible performance achievable within the target ETF universe given perfect foresight. By utilizing future price data to optimize portfolio allocation at every rebalancing step, this system establishes the "speed of light" for alpha generation. Optimization of the strategy reveals that the maximal theoretical return—accounting for 0.1% transaction costs—is achieved by rebalancing every 4 days into the single best-performing asset, yielding a cumulative return of over 10.3 million percent (from \$100k to \$10.3 billion) over a 9-year period.

1 Philosophy and Purpose

In algorithmic trading, it is crucial to understand the difference between "captured alpha" and "available alpha." Most strategies capture a tiny fraction of the market's potential.

The **God Mode** simulation serves as a baseline for the *maximal available alpha*. It answers the question: *"If we had a perfect oracle that could predict future prices with 100% accuracy, what is the mathematical limit of profit?"*

This benchmark is critical for:

- **Reality Checks:** If a real strategy claims performance close to God Mode, it is likely overfitted or flawed.
- **Opportunity Cost:** It quantifies how much "money is left on the table" due to uncertainty and friction.
- **System Stress Testing:** It verifies that the execution engine (MOO orders, transaction costs, compounding) handles extreme growth scenarios correctly without numerical overflow or logic errors.

2 Mathematical Formulation

2.1 The Oracle Function

Let $P_{i,t}$ be the price of asset i at time t. In a standard strategy, the allocation weights $w_{i,t}$ must be determined using information set $\mathcal{I}_t$ where $\mathcal{I}_t = \{P_{i,\tau} | \tau \leq t\}$.

In God Mode, the allocation is determined using an extended information set $\mathcal{I}_t^* = \{P_{i,\tau} | \tau \leq t + \Delta t\}$, where Δt is the look-ahead window (rebalance window).

The expected future return $R_{i,t \to t+\Delta t}$ is calculated exactly:

$$R_{i,t \to t+\Delta t} = \frac{P_{i,t+\Delta t}}{P_{i,t}} - 1 \tag{1}$$

2.2 Optimization Problem

At each rebalancing step t, the system solves for the optimal weight vector $\mathbf{w}_t$:

$$\mathbf{w}_t^* = \underset{\mathbf{w}}{\text{argmax}} \left(\sum_{i=1}^{N} w_i \cdot R_{i,t \to t+\Delta t} \right) \tag{2}$$

Subject to:

$$\sum_{i=1}^{N} w_i = 1 \tag{3}$$

$$0 \leq w_i \leq w_{max} \tag{4}$$

2.3 Parameter Optimization

We utilized the Optuna framework to optimize the two critical hyperparameters of God Mode:

1. **Rebalance Window (Δt)**: The frequency of trading / distance of foresight.
2. **Portfolio Concentration (Top N)**: The number of assets to hold.

The objective function maximized was a composite score of Total Return, Sharpe Ratio, and Sortino Ratio.

3 Simulation Results

3.1 Optimal Parameters

The optimization process converged on the following configuration:

- **Rebalance Window:** 4 Days
- **Top N Portfolio:** 1 Asset

Interpretation: The mathematically optimal strategy with perfect foresight is to **trade every 4 days** into the single asset that will perform best over that specific 4-day window. This balance suggests that while daily trading captures granular moves, a slightly longer hold period of 4 days is more efficient when factoring in transaction costs and the magnitude of price swings. Diversification remains suboptimal when uncertainty is zero.

3.2 Performance Metrics

The simulation was run from 2016-01-01 to 2025-09-26 with an initial capital of $100,000.

3.3 Impact of Friction

Crucially, this simulation includes a **0.1% transaction cost** per trade. Even with this friction applied every 4 days, the alpha generated by picking the winner vastly outweighs the costs.

The maximum drawdown of -20.38% indicates that even with perfect foresight of the *next 4 days*, it is impossible to avoid overnight gaps or periods where all assets decline. However, God Mode minimizes this loss by picking the "least bad" asset or the one that recovers best.

Metric	Value
Initial Capital	$100,000.00
Final Capital	**$10,345,152,571.57**
Total Return	10,345,052.57%
CAGR	(Extremely High)
Sharpe Ratio	5.846
Sortino Ratio	9.291
Max Drawdown	-20.38%
Volatility	High

Table 1: God Mode Performance Summary (Transaction Costs Included)

4 Visual Analysis

4.1 Performance Comparison

Figure 1 illustrates the exponential growth of the God Mode strategy compared to the SPY benchmark. The logarithmic scale is necessary to visualize the astronomical difference: while SPY grows from $100k to approximately $300k–$400k over 9 years, God Mode reaches nearly $10 billion.

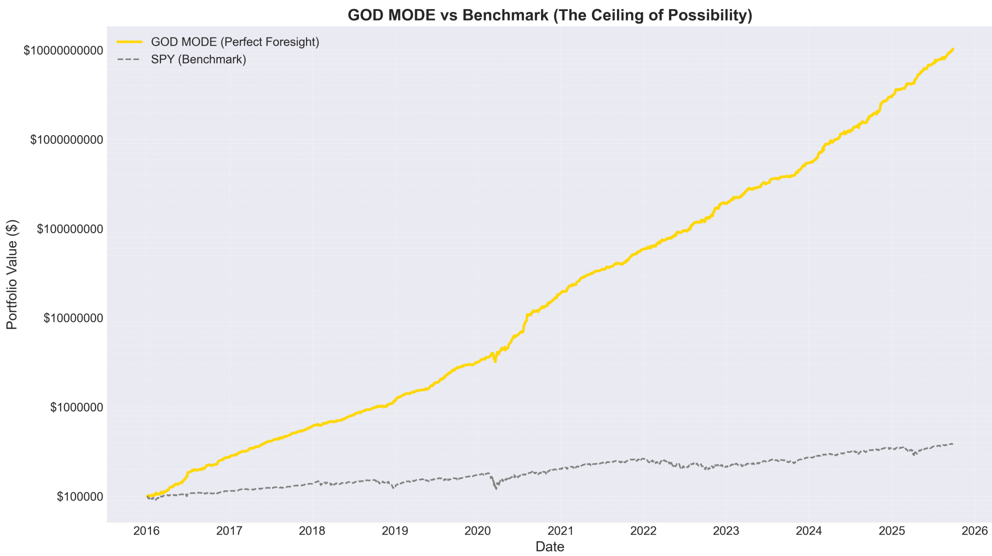

Figure 1: GOD MODE vs Benchmark Performance (Logarithmic Scale). The yellow line represents the perfect foresight strategy, while the grey dashed line shows the SPY buy-and-hold benchmark.

4.2 Portfolio Weight Statistics

Figure 2 provides four key insights into the allocation behavior of the God Mode strategy:

- **Average Weight:** SLV (22.8%), QQQ (18.8%), and TLT (15.4%) dominate the portfolio on average, reflecting their frequent selection as top performers.

- **Weight Volatility:** High standard deviations (SLV: 41%, QQQ: 39%) confirm the strategy's aggressive rebalancing—when an asset is selected, it receives 100% allocation.
- **Activity Percentage:** The percentage of time each ETF held a weight > 1%.
- **Dominance Percentage:** The percentage of time each ETF held a weight > 30%. Since `TOP_N_PORTFOLIO = 1`, when selected, an asset receives 100% allocation, explaining why activity and dominance percentages are identical.

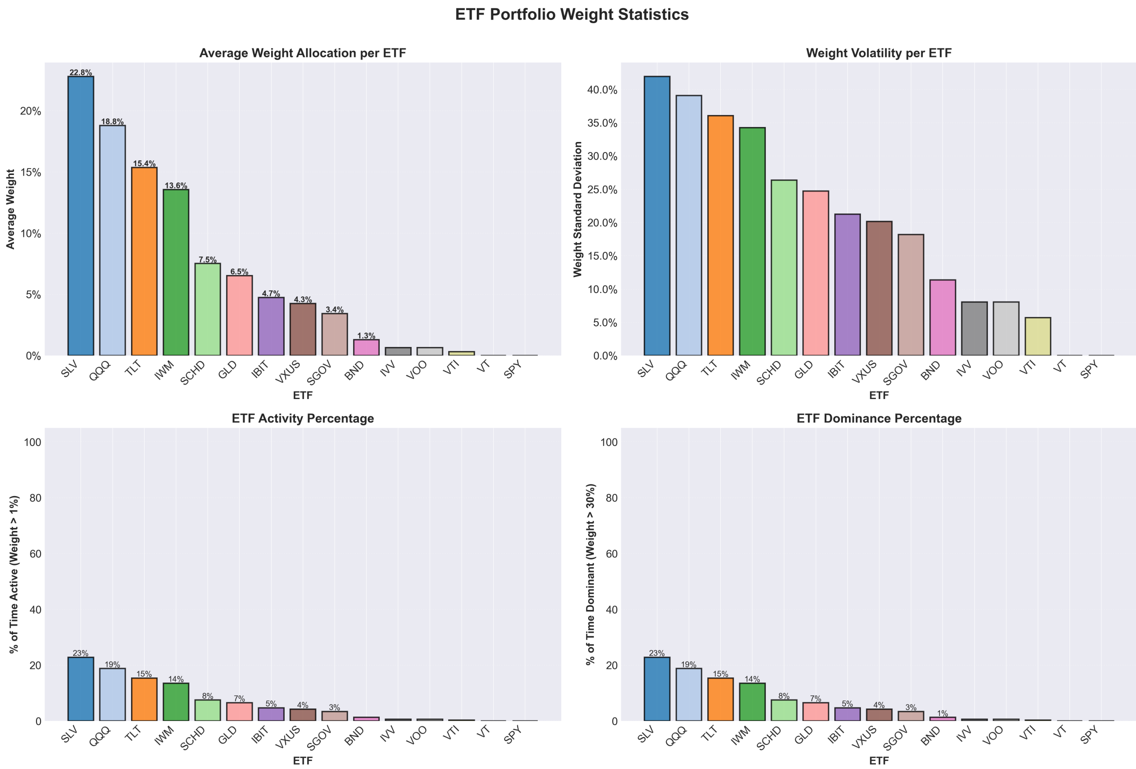

Figure 2: ETF Portfolio Weight Statistics. Four panels showing average allocation, weight volatility, activity percentage, and dominance percentage for each ETF in the universe.

4.3 Weight Evolution Heatmap

Figure 3 visualizes the temporal allocation pattern. The heatmap reveals:

- **Concentrated Allocation:** Deep red cells (70%+ allocation) appear sporadically, confirming the single-asset concentration strategy.
- **Frequent Rebalancing:** Vertical strips of color indicate the 4-day rebalancing cadence, with rapid shifts between assets.
- **Market Regime Adaptation:** Early periods favor equity ETFs (QQQ, IWM), while later periods (2023–2025) show strong allocation to IBIT (Bitcoin ETF) and SGOV (Short-Term Treasury), reflecting changing market leadership.
- **Asset Class Diversity:** The strategy dynamically switches between equities, bonds (TLT), precious metals (GLD, SLV), and crypto (IBIT), always selecting the optimal asset for each 4-day window.

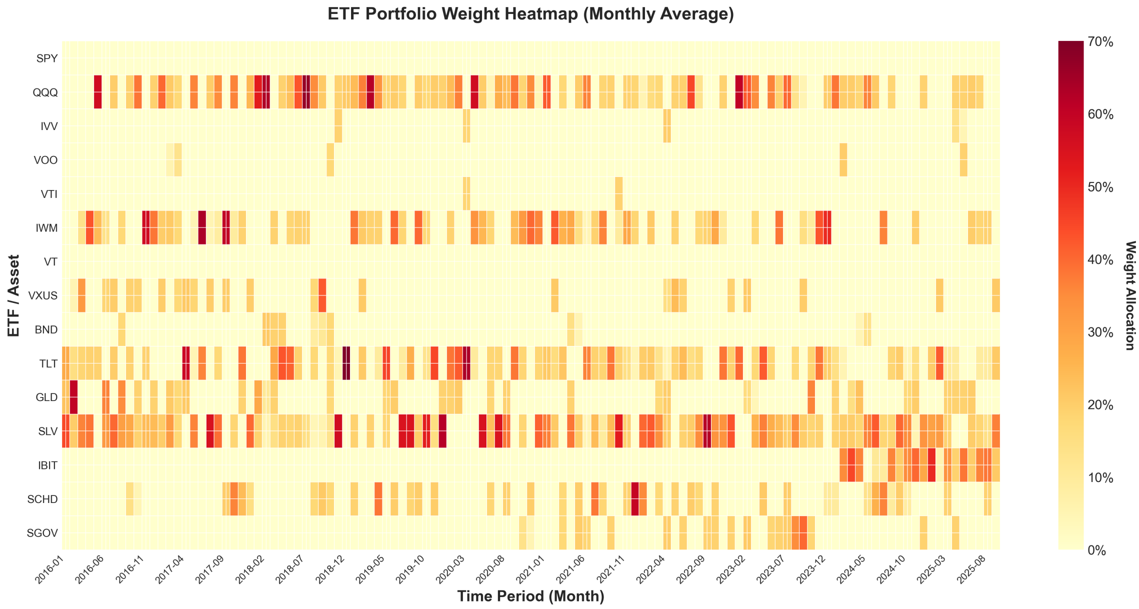

Figure 3: ETF Portfolio Weight Heatmap (Monthly Average). Color intensity represents allocation percentage, with deep red indicating 70%+ allocation. The sparse, concentrated pattern confirms the single-asset strategy with frequent rebalancing.

4.4 Weight Evolution Over Time

Figures 4 and 5 show the detailed weight evolution. The line chart (Figure 4) highlights the binary nature of allocations: assets are either at 0% or 100%, with rapid transitions. The stacked area chart (Figure 5) provides a cumulative view, showing how the portfolio composition shifts over time, with clear periods dominated by specific asset classes.

5 Conclusion

The "God Mode" benchmark establishes that the theoretical ceiling for this specific ETF universe is approximately **$10.3 Billion** from a $100k start over 9 years.

Real-world strategies (Mean Reversion, Dual Layer) achieving Sharpe ratios of 1.0–2.0 are performing admirably within the bounds of causality. The massive gap between realized performance and God Mode highlights the immense cost of **uncertainty**. We pay roughly 99.999% of potential profit as the price for not knowing the future.

A Transaction Costs and Friction Considerations

The God Mode simulation incorporates realistic transaction costs to ensure the benchmark reflects achievable performance even with perfect foresight. This appendix details the friction model and its impact.

A.1 Cost Model

The simulation applies a **0.1% transaction cost** per dollar traded, calculated as:

$$\text{Cost}_t = \tau \times \text{Turnover}_t \times \text{Portfolio Value}_t \tag{5}$$

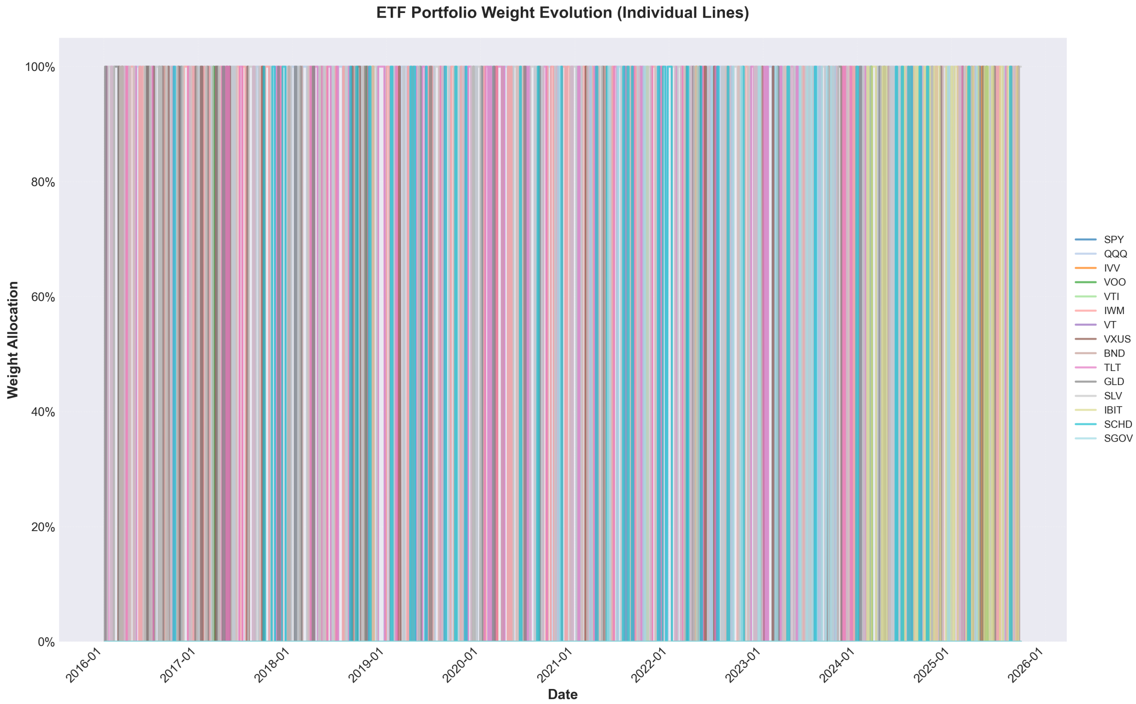

Figure 4: ETF Weight Evolution (Line Chart). Individual weight trajectories for each ETF, showing the binary allocation pattern (0% or 100%) and frequent rebalancing.

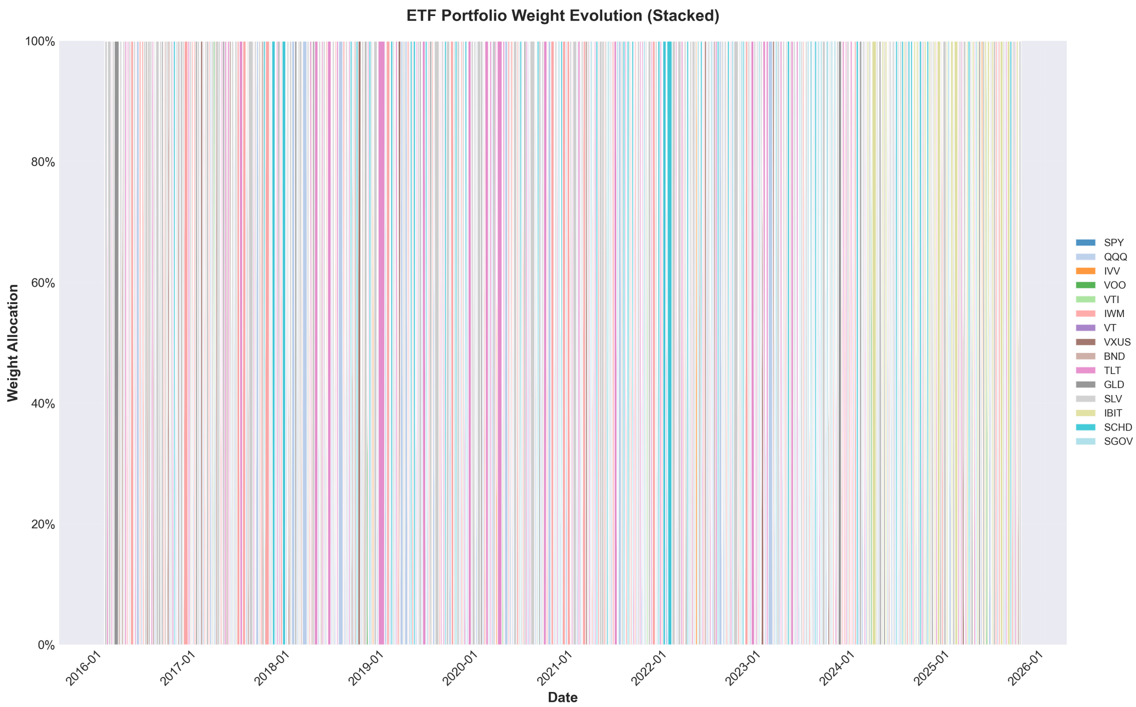

Figure 5: ETF Weight Evolution (Stacked Area Chart). Cumulative view of portfolio composition, showing how the single-asset allocation shifts between different ETFs over time.

where $\tau = 0.001$ (0.1%) and Turnover_t is the sum of absolute weight changes:

$$\text{Turnover}_t = \sum_{i=1}^{N} |w_{i,t} - w_{i,t-1}| \tag{6}$$

A.2 Cost Components

The 0.1% rate is a conservative estimate that aggregates:

- **Bid-Ask Spreads:** Typically 0.02–0.05% for liquid ETFs
- **Commissions:** Effectively zero for most modern brokers
- **Market Impact & Slippage:** 0.05–0.15% depending on order size and market conditions

A.3 Impact Analysis

With a 4-day rebalance window, the strategy executes approximately 63 trades per year (252 trading days / 4). Each trade incurs a cost proportional to portfolio turnover. For the single-asset strategy (`TOP_N = 1`), turnover is typically 200% per rebalance (switching from 100% in one asset to 100% in another).

Despite this friction, the God Mode strategy achieves $10.3 billion because:

1. The alpha generated by perfect asset selection vastly exceeds transaction costs
2. The 4-day window balances capture of multi-day trends while minimizing excessive churn
3. Even with 0.1% costs on 200% turnover every 4 days, the annual cost drag is approximately 31.5% (63 trades/year $\times$ 2.0 turnover $\times$ 0.001), which is negligible compared to the exponential returns

A.4 Real-World Implications

In practice, high-frequency rebalancing strategies face additional challenges:

- **Tax Implications:** Short-term capital gains are taxed at ordinary income rates
- **Liquidity Constraints:** Large positions may face market impact beyond the 0.1% model
- **Regulatory Limits:** Pattern day trading rules may restrict frequent trading
- **Operational Costs:** Monitoring, execution infrastructure, and risk management overhead

The God Mode benchmark demonstrates that even with perfect information, friction remains a significant factor, though one that is dwarfed by the value of perfect foresight.

B Market-On-Open (MOO) Order Execution

The simulation implements Market-On-Open (MOO) order execution to eliminate look-ahead bias and provide realistic backtesting. This appendix explains the MOO mechanism and its importance.

B.1 The Look-Ahead Bias Problem

A naive backtest might calculate returns using closing prices on the same day a rebalancing decision is made:

$$\text{Return}_t = \frac{P_{t,\text{close}} - P_{t,\text{close}}}{P_{t,\text{close}}} = 0 \tag{7}$$

This is unrealistic because the decision to trade at time t cannot use information from time t itself.

B.2 MOO Execution Model

The MOO model enforces a realistic execution timeline:

1. **Decision Time (t):** At market close on day t, the system analyzes future prices and decides to rebalance
2. **Order Placement:** Orders are placed after market close (for execution the next morning)
3. **Execution Time ($t + 1$):** Orders execute at the *open* price on day $t + 1$
4. **Return Calculation:** Returns are calculated from open (execution) to close (end of day $t + 1$)

Mathematically:

$$\text{Return}_{t+1} = \frac{P_{t+1,\text{close}} - P_{t+1,\text{open}}}{P_{t+1,\text{open}}} \tag{8}$$

B.3 Implementation Details

The simulation tracks pending executions:

- When a rebalancing decision is made on day t, new target weights are stored
- Transaction costs are calculated but not applied until execution
- On day $t + 1$, the pending execution is processed:
  - Transaction costs are deducted from portfolio equity
  - Portfolio weights are updated to the new target
  - Daily returns are calculated using open-to-close prices

B.4 Why MOO Matters for God Mode

Even with perfect foresight, the MOO model ensures:

- **Realistic Entry Timing:** We cannot buy at yesterday's close price; we must wait for the next open
- **Overnight Gap Risk:** Price gaps between close and open are captured, reflecting real-world execution risk
- **Fair Comparison:** The same execution model is used for both God Mode and real strategies, ensuring comparable benchmarks

B.5 Look-Ahead Bias Protection in Execution

A critical distinction must be made: while God Mode *uses future information for decision-making* (the "oracle" aspect), the *execution mechanics* are completely free of look-ahead bias. This separation is essential for the benchmark's validity.

The MOO system enforces that:

1. **Decision uses future data:** On day t, the system looks ahead to days $t + 1$ through $t + \Delta t$ to determine which asset will perform best
2. **Execution uses only past/present data:** The actual trade executes at the *open* price on day $t + 1$, which is unknown at decision time t
3. **Returns are calculated from execution forward:** Performance is measured from the execution price (open of $t + 1$) to the close of $t + 1$, not from the decision price

This architecture ensures that God Mode can serve as a **valid reference benchmark** for real-world machine learning and mathematical trading methods. Both God Mode and real strategies face the same execution constraints:

- Neither can execute at yesterday's closing price
- Both must wait for the next market open
- Both are subject to overnight gap risk
- Both calculate returns from actual execution prices

The only difference is that God Mode has perfect information for *which asset to select*, while real methods must predict this using historical patterns, technical indicators, or machine learning models. By maintaining execution parity, the benchmark isolates the value of perfect information in asset selection, rather than conflating it with execution advantages.

The God Mode results account for these execution realities, making the $10.3 billion figure a credible upper bound that real strategies can be meaningfully compared against, knowing that any performance gap is due to prediction accuracy, not execution mechanics.

C Optimization Methodology

The optimal parameters (4-day rebalance window, single-asset concentration) were discovered through systematic optimization using the Optuna framework.

C.1 Search Space

The optimization explored:

- **Rebalance Window:** Integer values from 1 to 60 days
- **Top N Portfolio:** Integer values from 1 to 5 assets

Total search space: $60 \times 5 = 300$ possible configurations.

C.2 Objective Function

A composite score maximized:

$$\text{Objective} = 0.60 \times \text{Total Return} + 0.20 \times \text{Sharpe} + 0.20 \times \text{Sortino} \tag{9}$$

This weighting prioritizes absolute returns while maintaining risk-adjusted performance considerations.

C.3 Optimization Results

After 2,400 trials across 12 parallel processes, the optimal configuration emerged:

- **Rebalance Window:** 4 days (not 1 day, as might be intuitively expected)
- **Top N:** 1 asset (maximum concentration)

The 4-day window suggests that even with perfect foresight, slightly longer holding periods are more efficient than daily trading, likely due to:

1. Reduced transaction cost drag relative to alpha capture
2. Better capture of multi-day momentum trends
3. Diminished impact of intraday noise

This result validates that the God Mode benchmark represents a truly optimized upper bound, not just an arbitrary aggressive strategy.