Adaptive Optimization of an Enterprise Investment Portfolio Based on Market Regime Identification Using Artificial Intelligence

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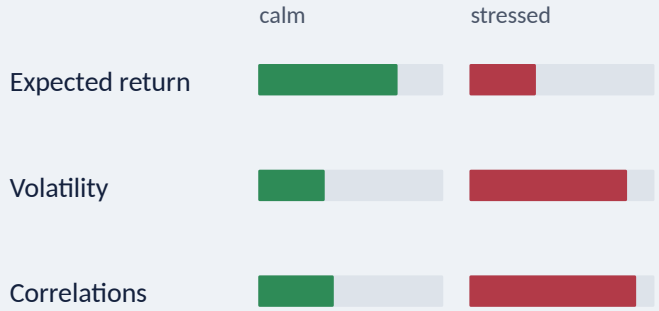
Why static portfolio models fall behind

1. **Markets are non-stationary**
   Expected returns, volatility and cross-asset correlations shift with the market state

2. **A good portfolio ages badly**
   Weights optimized under one set of conditions lose their risk–return fit once the environment changes

3. **Fixed parameters = static management**
   A model with unchanging risk settings cannot react to new market conditions

The same portfolio, two market states



Weights that were optimal on the left are no longer optimal on the right — unless the model's parameters move too

Research gap. In most regime-based approaches the identified regime dictates asset weights directly. The mechanism that transmits the regime signal into the parameters and constraints of the optimization model remains underformalized.

From Markowitz to AI-driven regime awareness

1952

Mean–variance foundation

Markowitz: quantitative balancing of return and risk

2004–2007

Regime-dependent allocation

Ang & Bekaert; Guidolin & Timmermann: market phases differ in volatility, correlations and opportunities

2018

Hidden regimes in practice

Nystrup et al.: dynamic optimization across hidden market regimes

2020–2026

AI for portfolio decisions

Jiang et al.; Sutiene et al.; Dastkhan et al.: machine learning for regime signals and dynamic rebalancing

RESEARCH AIM

To substantiate an approach to adaptive enterprise portfolio optimization in which the market regime identified by an AI module drives regime-dependent tuning of the risk parameters and constraints of the portfolio model

Architecture: the regime as a control signal

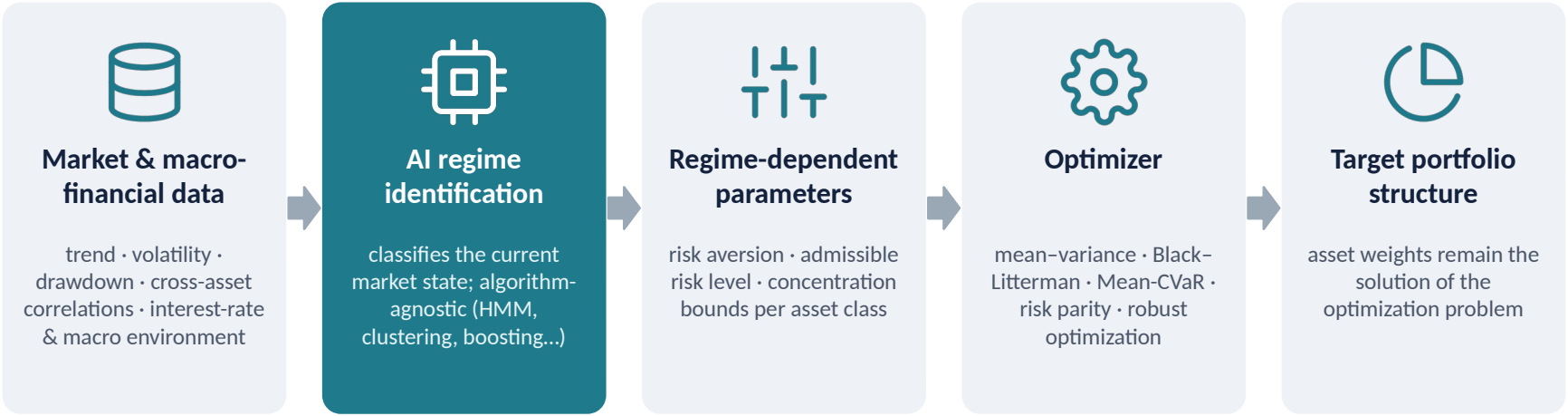


Fig. 1 adapted from the theses: adaptive portfolio optimization sequence

Key idea. The identified regime does not prescribe asset weights. It changes the conditions under which the optimization problem is solved — the AI module reads the market, the optimizer builds the portfolio.

Four market regimes and the policy response

Regime	Market characteristics	Portfolio policy response
S1 **Growth**	Positive dynamics, favourable risk–return ratio	Lower risk aversion; higher exposure to risky assets to capture the risk premium
S2 **Elevated volatility**	Rising uncertainty without a systemic crisis	Gradual tightening of risk constraints; reduced concentration of risky assets
S3 **Crisis**	Negative dynamics, deep drawdown, assets move together	Most conservative parameters; capital preservation takes priority
S4 **Neutral**	No pronounced upward or downward trend	Balanced configuration of risk parameters

Volatility ≠ crisis

Elevated volatility signals uncertainty, but not a systemic breakdown. A crisis combines negative returns, deep drawdown and the loss of diversification at once.

The response to S3 must therefore be stronger than to S2.

Why this design: modular, transparent, adaptable

Modular

The regime changes parameters and constraints, not the optimizer. The AI classifier can be replaced without rebuilding the loop.

Transparent

Every decision is traceable — market state → adjusted risk constraints → portfolio structure. No pre-set weights hidden in a black box.

Adaptable

Fits enterprise portfolios of different composition, data availability and risk-management policy.

Traceable decision chain



Conclusions

1. **Adaptive optimization as an interaction** of intelligent market-state analysis and economic-mathematical portfolio formation — not a replacement of one by the other.

2. **The regime is a control signal, not a weight signal** — it tunes risk aversion, admissible risk and concentration bounds, while asset weights remain the optimizer's solution.

3. **A four-regime operational typology** (growth, elevated volatility, crisis, neutral) with an explicit S2/S3 distinction formalizes graded portfolio responses without binding the framework to one AI or optimization method.

Next step: empirical comparison of regime-identification methods and optimization models within the proposed adaptive loop

Thank you

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