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Elimination of Financial Bubbles Exposure and Tactical Leadership Bias in the risK-Yield Discriminant OptimizatioN—KYDON

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Abstract

The novel risK-Yield Discriminant OptimizatioN—KYDON can optimize portfolio selection in a volatile market, eliminating the exposure to extreme events: bubbles and busts. Implementing novel methods such as: (i) chaos dynamics, (ii) behavioral welfare, and (iii) optimal AI classifiers, KYDON supports the optimal investment policy. It diagnoses the possibility of bubbles, prepares for their burst under expectations of long growth and reduces the impact of systemic risk. KYDON performs as a dragonslayer, eliminating the loss of investors.

Keywords: logic; free will; Aristotle; Epicurus; leadership; naval supremacy; modular; support vector machines entropy; kappa distributions; tsallis statistics; fractal market hypothesis; portfolio optimization

1. Introduction

Market fluctuations become stronger in periods of instability. Influenced by economic and geostrategic frictions, they usually produce crashes. Distinct groups of interests seek to dominate the markets based on their agenda. This imbalance of interests supports a plethora of irrational expectations. Thus, future returns tend to be inadequately priced, much further than the evaluations of current models. Thus, policymakers and some fund managers detect these instabilities and invest in burgeoning bubbles. They collect overpriced securities and sell them later on at overvalued prices for extreme profits, contradicting the markets. In this research study, the analytical model risK-Yield Discriminant OptimizatioN—KYDON is introduced, inspired by my previous models, HERACLES and PYR, and my past model EPICO, which outperformed the S&P 500 by 7.5%. I extended my research under the evolved KYDON model to act as a dragonslayer that protects investors from exposure to crashes that follow bubbles. Extended tools in terms of gain and pain are incorporated, with the advanced prospect of chaotic entropy, fundamental filtering, investor sentiments, and behavioral welfare to optimize investments.

The price equilibrium set by demand and supply on heterogenous investors with different levels of information is essential for efficiency on the markets. The rational expectations of positive growth lead investors; thus, markets evaluate future perspectives. Additionally, the markets incorporate deposits of value. In the case of growth, the gains increase on the markets, boosting consumption and the circulation speed of money, introducing a phase of development.

The phenomenon of excess volatility belongs to the usual behavior of the markets, as exuberant phases may cause crashes. Multiple situations have put the markets in turmoil:

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the 1986 London flood that inspired the Soros attack on the GBP, the 1998 LTCM crash, the 1998 dot-com boom and 2001 crash, the 2003 boom and 2006 toxic bonds crash, the 2009 Greek crisis, the COVID 2020 crash, etc.

The optimization of a portfolio is an essential challenge in finance, as the balance between returns and risk, further extended to advanced higher moments, is critical. Current models are usually not quite analytical in regard to the investor's behavioral patterns and the idiosyncrasies of the markets, like those that the Fractal Market Hypothesis examines.

Dou et al. (2020) introduce a customer capital model depending on key talents ad brand recognition. The stability of customer capital demand is risk-sensitive if expressed by talents that usually drop distressed firms, thus creating the Inalienability of Customer Capital (ICC), offering a measure of dependence on customer capital that depends on talents. The firm-level measure of the firms with higher ICC has higher average returns, talent turnover, and precautionary financial policies, and with the financial constraints factor sorted, the long-short portfolio's spread comoves. Kelly et al. (2023) reviewed the state of the art of AI portfolio management applications in terms of algorithmic type, databases characteristics, balance, and cardinality, revealing that evolutionary algorithms, fuzzy models, and hybrid models of two or more algorithms used simultaneously are efficient. Limited RL algorithms use, among others, low unconventional assets in the portfolios: one work showed cryptocurrencies and no commodities or currencies and indices. They analyzed return and risk in regard to assets, frequency, period analyzed, etc., suggesting deep learning algorithms in conjunction with RL techniques and evolutionary algorithms.

Bonaime and Wang (2024) surveyed CFO perspectives on shareholder versus stakeholder focus, capital structure, investment, corporate planning, and payout in a comparative analysis of policy today compared to 20 years ago and found that firms make conservative decisions, geared to time the market, stick to and, rely on internal miscalibrated forecasts that are reliable only two years forward, emphasizing corporate objectives that increasingly focus on revenues and stakeholders. Graham (2022) introduced a conditional factor model to corporate bond returns in five time-varied factors and concluded with three empirical findings: (i) their factor model exceled in the returns and risks of corporate bonds by a large margin over proposed models; (ii) it suggested a systemic bond portfolio of a superior out-of-sample Sharpe ratio of higher credit risk premiums than previously estimated; (iii) they found closer integration between debt and equity markets than prior literature. Kogan et al. (2023) examined different intelligent, statistical, and classical models for portfolio optimization, as well as recent advances in machine learning and artificial intelligence, to support portfolio manager decision-making, compiling quantum, intelligent, and classical models, and concluding that evolutionary optimization has superior performance in portfolio optimization. The evolutionary-quantum techniques offer more viable alternatives. Puri (2025) showed variable production costs minimize systemic cash flow risk if the capital and variable inputs are complementary in company production and procyclical input prices. They modeled simulated moments for stock returns and cash flows consistent with the data. Their dynamic model had a weaker operating hedge effect for more profitable firms, with a rising gross profitability premium that was distinct and negatively correlated to value factors, as their premia are not given in Capital Asset Pricing Model (CAPM).

Abhishek and Bhattacharyya (2023) implemented new data from the pharmaceutics industry on product prices and merger innovation and showed that prices increase more for drugs on consolidated markets than for matched control drugs. Trade-offs revealed that these deals generate significant shareholder value. Smith and Kevin (2024) explored a hybrid approach to portfolio optimization that integrated the strengths of AI algorithms, machine learning (ML) and reinforcement learning (RL), with traditional statistical techniques: mean-variance optimization (MVO) and CAPM, improving portfolio performance and risks in

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hybrid AI-statistical models, demonstrating how the model can adapt to market fluctuations, predict optimal asset allocations, and outperform traditional portfolio optimization methods. The results indicate that the hybrid approach offers superior risk-adjusted returns, providing a robust tool for investors seeking to optimize their portfolios.

Santos et al. (2022) introduced and tested a preference for simplicity in choice under risk, characterizing the theory axiomatically and deriving its properties and unique predictions relative to canonical models. People prefer simple forms that have not been described yet in the literature on risk premia in finance: their risk premia increase as complexity increases, holding moments fixed, their complex dominance violations increase, and the behavior is predicted by a characterizing axiom of simplicity in heterogenous aversion of complexity in cognition. Neither cumulative prospect theory, expected utility theory, rational inattention, prospect theory, salience, sparsity, nor probability weighting differences in outcomes fully capture the experimental findings. Santos et al. (2022) generalized to capture the broader measures of complexity, including obfuscation, computation, and language effects.

This research introduces KYDON, an innovative model to resolve cases by detecting the best classifier on neural and hybrid models, ensuring a higher portfolio outcome. It also evaluates the effectiveness of the first step that conducts a hierarchical ranking of portfolios to resolve the second step that analyzes advanced moments of risk and returns to optimize the portfolio. The second step of the portfolio selection analyses the detailed norms of returns (expected return, skewness, hyper-skewness, ultra-skewness) and risk (volatility, kurtosis, hyper-kurtosis, ultra-kurtosis, etc.) (Loukeris et al. 2021). The first step produces a hierarchical ranking of portfolios and the feasible set, which will later result in an excellent portfolio (Loukeris and Eleftheriadis 2024; Loukeris et al. 2024). In this research I examine the first step to resolve the second step, comparatively analyzing 40 Modular Networks (MDNs) on 10 neural and 30 hybrid MDNs and 6 Support Vector Machines (SVMs) on 2 plain SVMs and 6 hybrid SVMs, on multiple topologies, to define the best classifier in portfolio selection. This research aims to:

Provide an effective tool to incorporate the detailed behavioral preferences of investors (Shiller 2006);

Contribute to the portfolio theory, elaborating hidden data of accounting statements and investor sentiments on the fundamentals, minimizing bias, and selecting healthy securities in the substratum of the chaos and fractal market hypothesis;

Evaluate the MDN and SVM networks in various forms of neural or hybrid systems to have the best classifier in portfolio selection.

2. Exuberance on the Markets by Free Will?

Excess volatility periods (Sornette 2003) are a usual pattern on the markets, producing overpriced/underpriced assets and thus slots of exuberance that emerge probabilistically (Sornette and Cauwels 2015; Kristoufek 2013). The core of this research is with KYDON to decrease the exposure to excess volatility without neglecting the growth opportunities on the markets. Loukeris and Eleftheriadis (2024) and Loukeris et al. (2024) addressed the principal problem of logic implemented in the portfolio optimization. Loukeris et al. (2021), Loukeris and Eleftheriadis (2024) and Loukeris et al. (2024) revealed that logic has a linear dynamic fitness and can readjust, overriding the innovative challenges of superior gain in less pain achievements on short memory.

Higher welfare opportunities are attainable simply but are more complicated than plain linear processing. Physical logic optimizes the usefulness and behavioral well-being of investors. The induction of Aristotelian logic and the hedonistic (serene) Epicureanism elaborated by Loukeris et al. (2021), Loukeris and Eleftheriadis (2024) and Loukeris et al.

(2024) emphasized that usual routine behavior can be altered to dynamic logic aiming for superior perspectives.

Heterogeneous information and the substratum of investors exposed to emotional bias may have irrationality. The dynamic models of non-linearity in extended complexity fit as the Fractal Markets Hypothesis (Peters 1952; Subrahmanyam 2008). Currently the shocks of the Ukraine–Russia war, the Hamas–Hezbolah–Israel war, and the Israel–Iran–USA war increase volatility, meaning short-term investments are better.

The time series of prices behave as fractals, as FMH explains (Maringer and Parpas 2009), and in periods of shock, the higher volatility and its uncertainty produce instant bubbles and bursts. They are affected by time and changes in information.

Investors are more interested in their potential losses Subrahmanyam (2008); chaotic market chaotic dynamics can support more efficient investments. The returns advance moments incorporating detailed aspects of the behavior of investors of risk averse absolute hyperbolic (HARA) utility by Loukeris et al. (2021), Loukeris and Eleftheriadis (2024), and Loukeris et al. (2024):

$$U_t(R_{t+1}) = \sum_{\lambda_v=1}^{\omega} \left(-1\right)^{\lambda_v+1} \frac{a_{\lambda_v}}{n} \sum_{i=1}^{n} \left(r_i - \sum \frac{r_i}{n}\right)^n \tag{1}$$

where λ_v represents precision risk preferences, $a_{\lambda v}$ the level of risk-aversion (1: rational speculators, $\neq$1 non-rational), and r_i the return on stock i. The HARA isoelastic utility:

$$U = \begin{cases} \frac{W^{1-\lambda}-1}{1-\lambda}, & \lambda \in (0,1) \cup (1,+\infty] \\ log(x) & for\ \lambda = 1 \end{cases} \tag{2}$$

where W is wealth. The Markowitz model, as a quadratic utility, is a typical Epicurean Aponia (Sornette 2003):

$$\min_x f(x) = \lambda Var(r_p) - (1-\lambda)E(r_p) \tag{3}$$

where x_i is the rate of asset i in the portfolio and r_p is the return of the portfolio. The long-memory effects on market non-linearity are explained by the entropy of chaos in Kullback–Leibler relative entropy (KLRE). KLRE describes systems of non-extensive behavior Kristoufek (2013). The kappa distributions in the generic norm of KLRE and their subset of Tsalis statistics were evaluated on Loukeris et al. (2024), Markowitz (1952), Tsallis (1988), Rak et al. (2007), Zhao et al. (2021), Kohonen (1982).

The distance to the default point (DD) is where the asset's value equals its total liabilities. Debts are short-term (STD) or long-term (LTD):

$$DP = STD + \beta LTD \tag{4}$$

The fractal distribution is a probabilistic self-similarity distribution over its parts and the whole in different scales. Fractals are natural phenomena that also take place on the markets. The fractals demonstrate non-linear characteristics and complex dynamic behaviors, thus are more precise in the valuation of the return and risk in portfolios. To incorporate the fractal characteristics of return and risk, two fractal indicators are created: fractal expectation and fractal variance.

The methods are as follows (Freund and Schapire 1999): in the price trajectory with endpoints x_0 and x_T, let e = $d(x, y)$ be the distance between points x and y, as x_1 and x_2, the conditions $d(x_0, x_1) = \varepsilon$ and $d(x_1, x_2) = \varepsilon$ hold. If $d(x_n, x_T) \leq \varepsilon$ holds, the length of the trajectory is $L(\varepsilon) = \varepsilon n(\varepsilon)$. If ε is smaller, the curve length will be more accurate. The conventional approach shows that when $\lim_{\varepsilon\to 0} L(\varepsilon) = L \to 0$, L: length of the trajectory, as $\lim_{\varepsilon\to 0} L(\varepsilon) \to \infty$, L is invalid.

The fractal solution has values of d and m: $\lim_{\varepsilon\to 0} L(\varepsilon) \to \infty$, $\lim_{\varepsilon\to 0} m^{-1}\varepsilon^d n(\varepsilon) = 1$ hold, $L(\varepsilon) \approx m\varepsilon^{1-d}$ exists, d, $m \in R^+$ are the fractal dimension and Minkowski capacity of the curve. The expectation is $E(X) = \lim_{c\to\infty} E_c(X)$, of $E_c(X) = \int_{-c}^{c} x\rho(x)dx$, where $\rho(x)$ is the density function, as the returns follow a fractal allocation. A fractal distribution incorporates four variables: (i) characteristic, (ii) skewness, (iii) scale, and (iv) location in higher complexity. If the characteristic is less than 2 and the skewness is 0, the tail of the variable exhibits a fractal distribution. Hence $\rho(x)$: for $x \geq x_0$, $\rho(x) = \rho_0\, x^{-a}$; and for $x < x_0$, $\rho(x) = 0$. $c\in R^+$: $c > x_0$, $a \neq 2$, then it must hold (Freund and Schapire 1999; Li and Wu 2025).

If $a > 2$, $E_c(X)$ is finite, $\exists\, E(X)$, otherwise, if $a < 2$, $E_c(X) \to \infty$, thus expected value $E(X) \to \infty$.

$$E_c(X) = \int_{-c}^{c} x\rho(x)dx = \int_{-c}^{c} \rho_0 x^{1-\alpha}dx = \frac{\rho_0}{2-a}\left(c^{2-a} - x_0^{2-a}\right) \tag{5}$$

when $E(X)$ is finite and valid. In the fractal. $E(X)$ depends on $\langle E_X,\ e_X\rangle$, thus $E_f(X) = \langle E_X,\ e_X\rangle$ is the fractal expectation:

$$\lim_{c\to\infty}(2-a){\rho_0}^{-1}c^{a-2}E_c(X) = 1 \tag{6}$$

As $\{\alpha_\iota\}_{\iota=1}^{n}$: n is constants and $n\{X_\iota\}_{\iota=1}^{n}$: n is random variables, the fractal expectation $E_f(X_i)$ of the i-th random variable X_i follows.

$$\left\{\begin{array}{c} E_f(X_i) < E_f(X_j) \Leftrightarrow \left(e_{X_i} < e_{X_j}\right) \vee \left[(e_x = e_x) \wedge \left(E_{X_i} < E_{X_j}\right)\right. \\ E_f(X_i)E_f(X_j) = \left\langle E_{X_i} < E_{X_j},\ e_{X_i} + e_{X_j}\right\rangle \\ E_f\left(\sum\limits_{\iota=1}^{n} a_\iota X_i\right) = \sum\limits_{\iota=1}^{n} a_\iota E_f(X_i) = \langle \sum\limits_{\iota=1}^{m} a_{i_k} E_{X_{i_k}}, e_{X_\eta}\rangle,\ e_{i_1} = \cdots = e_{i_m} = \max\{e_i\}_{i=1}^{n} \\ E_f(X_i)\left[E_f(X_j)\right]^{-1} = \left\langle E_{X_i}E_{X_j}^{-1},\ e_{X_i} - e_{X_j}\right\rangle \\ \left[E_f(X_i)\right]^q = \left\langle E_{X_i}^q q e_{X_i}\right\rangle,\ \forall i \neq j \in \left\{1, \ldots, n_{i_k}\right\} \end{array}\right\} \tag{7}$$

The variance is $\mathrm{Var}(X) = \lim_{c\to\infty} E_c^2(X) - [\lim_{c\to\infty} E_c(X)]^2$ if $a \neq 3$ (Freund and Schapire 1996; Li and Wu 2025). Similarly, if $a \neq 2$ and $a \neq 3$, the variance follows, in $a < 3$: $Var(X) \to \infty$, Sun et al. (2004), holds; when $a > 3$ and $Var(X)$ is finite, it still holds. Thus, in the fractal perspective $Var_f(X) = \langle V_x, v_{X_i}\rangle$ is the fractal variance.

$$\lim_{c\to\infty} E_c^2(X) = \lim_{c\to\infty}\int_{-c}^{c} x^2\rho(x)dx = \frac{\rho_0}{3-\alpha}\left(c^{3-a} - x_0^{3-a}\right) \tag{8}$$

$$\mathrm{Var}(X) = \lim_{c\to\infty}\left[\frac{\rho_0}{3-\alpha}\left(c^{3-a} - x_0^{3-a}\right) - \frac{\rho_0^2}{(2-\alpha)^2}\left(c^{4-2a} + x_0^{4-2a} - 2c^{2-a}x_0^{2-a}\right)\right] \tag{9}$$

$$\left\{\begin{array}{c} \lim\limits_{c\to\infty}(3-\alpha)\rho_0^{-1}c^{\alpha-3}Var(X) = 1,\ a > 1 \\ \lim\limits_{c\to\infty}\left(2-a\right)^2\rho_0^{-2}c^{2\alpha-4}Var(X) = 1,\ a < 1 \\ \lim\limits_{c\to\infty}\left(2^{-1}\rho_0 - \rho_0^2\right)^{-1}c^{-2}Var(X) = 1,\ a = 1 \end{array}\right\} \tag{10}$$

$$V_x, v_x = \left\{\begin{array}{c} \left(3-a\right)^{-1}\rho_0,\ 3-a,\ a > 1 \\ 2^{-1}\rho_0 - \rho_0^2,\ 2,\ \alpha = 1 \\ \left(2-a\right)^{-2}\rho_0^2,\ 4-2a,\ a < 1 \end{array}\right\} \tag{11}$$

$Var_f(X_i)$ is the fractal variance of random variable X_i and follows operational rule (12). The fractal variance does not use covariances and $Var_f(X)[\sum_{i=1}^{n}\alpha_i X_i] < \sum_{i=1}^{n}\alpha_i Var_f(X_i)$

when $\sum_{i=1}^{n} \alpha_i = 1$ and $a_i > 0$. Thus, the fractal variance incorporates the risk diversification in the portfolio.

$$\begin{cases} Var_f(X_i) < Var_f(X_j) \Leftrightarrow \left(v_{X_i} < v_{X_j}\right) \vee \left[\left(v_{X_i} < v_{X_j}\right) \wedge \left(V_{X_i} < V_{X_j}\right)\right. \\ Var_f(X_i)Var(X_j) = \left\langle V_{X_i} < V_{X_j}, v_{X_i} + v_{X_j} \right\rangle \\ Var_f\left(\sum_{\iota=1}^{n} a_\iota X_i\right) = \sum_{\iota=1}^{n} a_i^2 Var_f(X_i) = \langle \sum_{\iota=1}^{m} a_{i_k}^2 V_{X_{i_k}}, v_{X_\eta} \rangle,\ v_{i_1} = \cdots = v_{i_m} = \max\{v_i\}_{i=1}^{n} \\ Var_f(X_i)\left[Var_f(X_j)\right]^{-1} = \left\langle V_{X_i} V_{X_j}^{-1}, v_{X_i} - v_{X_j} \right\rangle \\ \left[Var_f(X_i)\right]^q = \left\langle V_{X_i}^q q v_{X_i} \right\rangle,\ \forall i \neq j \in \{1, \ldots, n_{i_k}\},\ \forall q \in R^+ \end{cases} \tag{12}$$

After introducing the two fractal statistical measures, the portfolio is created assigning weights to different assets to maximize the Sharpe return–risk ratio. The portfolio P is composed of n assets $\{Y_i\}_{i=1}^{n}$ with weights $\{\omega_i\}_{i=1}^{n}$, and the return r_{exc,i_t} on the assets is $\{r_{exc,i_t}\}_{i=1}^{n}$. The investment portfolio is created resolving for the investment weights $\{\omega_i\}_{i=1}^{n}$, maximizing the return risk:

$$\begin{cases} \min Var(r_p) = \min\left\{ \sum_{\iota=1}^{n} \omega_i^2 Var(r_{i_t\ i}) + \sum_{\iota=1}^{n} \omega_i \omega_j Cov(r_{i_t\ i}, r_{i_t}) \right\} \\ \text{Constraint Condition} \begin{cases} \sum_{\iota=1}^{n} \omega_i = 1 \\ max\frac{u}{V} \\ \omega_i > 0 \end{cases} \end{cases} \tag{13}$$

$$\left\{ \begin{cases} w_i = \frac{u\sum_{\iota=1}^{n} \theta_{ij} + \left[\left[\sum_{\iota,j=1}^{n} \theta_{ij}\right] r_j - \sum_{\iota,j=1}^{n} \theta_{ij} r_j\right] + \sum_{j=1}^{n} \theta_{ij}\left[\sum_{\iota,j=1}^{n} \theta_{ij} r_i r_j - \left(\sum_{\iota,j=1}^{n} \theta_{ij} r_j\right) r_j\right)\right]}{\left(\sum_{\iota,j=1}^{n} \theta_{ij} r_i r_j\right)\left(\sum_{\iota,j=1}^{n} \theta_{ij}\right) - \left(\sum_{\iota,j=1}^{n} \theta_{ij} r_j\right)^2} \\ \begin{bmatrix} \theta_{11}\ \theta_{12} \ldots \theta_{1n} \\ \theta_{21}\ \theta_{22} \ldots \theta_{2n} \\ \vdots \\ \theta_{n1}\ \theta_{n2} \ldots \theta_{nn} \end{bmatrix} = \begin{bmatrix} Var(r_{1_t})\ Cov(r_{1_t}, r_{2_t}) \ldots Cov(r_{1_t}, r_{n_t}) \\ Cov(r_{2_t}, r_{1_t})\ Var(r_{2_t}) \ldots Cov(r_{2_t}, r_{n_t}) \\ \vdots \\ Cov(r_{n_t}, r_{1_t})\ Cov(r_{n_t}, r_{2_t}) \ldots Var(r_{n_t}) \end{bmatrix}^{-1} \end{cases} \right\} \tag{14}$$

The MTP and the model create a portfolio on fractal expectation and fractal variance. For a portfolio P of n assets $\{\mathrm{Y_i}\}_{i=1}^{n}$ and weights $\{\omega_i\}_{i=1}^{n}$, as $E_f(r_i) = E_i, e_i$ and $E_f(r_p) = E_p, e_p$ the fractal expectations of asset i are Y_i and portfolio P. The fractal variances of assets and the portfolio are $Var_f(r_p) = V_p, v_p$, and of the return are:

$$\begin{cases} \min Var_f(r_p) = \min\left\{ \sum_{\iota=1}^{n} (\omega_i^f)^2 Var_f(r_{i_t\ i}) \right\} \\ \text{s.t.} \begin{cases} \sum_{\iota=1}^{n} \omega_i^f = 1 \\ max\frac{u}{V} \\ \omega_i > 0 \end{cases} \end{cases} \tag{15}$$

The solution in the Lagrange technique finds the conditional extremum of the objective function based on the given constraints. Thus, the optimal portfolio of fractal expectation and variance $\{\omega_i^n\}_{i=1}^{n}$ reflects the weights of the assets $\{\mathrm{Y_i}\}_{i=1}^{n}$

$$L\left(\omega_1^f, \ldots, \omega_n^f, \lambda_1, \lambda_2\right) = Var_f(r_p) - \lambda_1\left\{\sum_{\iota=1}^{n} \omega_i^f E_f(r_{i_t}) - \mathrm{u}\right\} - \lambda_2\left(\sum_{\iota=1}^{n} \omega_i^f - 1\right) \tag{16}$$

$$\begin{cases} 2\omega_i^f Var_f(r_{i_t}) = \lambda_1 E_f(r_{i_t}) + \lambda_2 \\ \sum_{\iota=1}^{n} \omega_i^f = 1 \\ E_f\left(\sum_{\iota=1}^{n} \omega_i^f\right) = \sum_{\iota=1}^{n} \omega_i^f E_f(r_{i_t}) = u \end{cases} \tag{17}$$

$$\text{Constraint Condition} \begin{cases} \sum_{\iota=1}^{n} \omega_i = 1 \\ max\frac{u}{V} \\ \omega_i > 0 \end{cases} \tag{18}$$

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$$\begin{cases} \omega_i^f = \frac{(1-\varphi\psi+\varphi\varphi u)E_f(r_i)}{2\varphi Var_f(r_i)} + \frac{\psi-\varphi u}{2(\varphi\psi-\varphi^2)Var_f(r_i)} \\ \sum_{\iota=1}^n \omega_i^f = 1 \\ \varphi = \left(\sum_{\iota=1}^n \frac{E_f\left(r_{i_t}\ \right)}{2Var_f\left(r_{i_t}\ \right)}\right),\ \varphi = \sum_{\iota=1}^n \frac{1}{2Var_f\left(r_{i_t}\ \right)},\ \psi = \sum_{\iota=1}^n \frac{\left[E_f\left(r_{i_t}\ \right)\right]^2}{2Var_f\left(r_{,i_t}\ \right)} \end{cases} \quad (19)$$

To adapt to the practical needs of commercial bank credit management, it is necessary to convert the credit asset weights from an array to numerical data. We can denote this as $\omega_i^f = \langle W_1, w_1 \rangle$, and based on the definitions of fractal expectation and fractal variance, we obtain that $lim\omega_i^f W_i^{-1} c^{-w_i} = 1$ holds. On a sufficiently large c, $\omega_i^f \approx W_i c^{w_i}$ is valid and thus $\omega_i^f \approx \left(W_i c^{w_i} \left(\sum_{i=1}^n W_i c^{w_i}\right)^{-1}\right)$ transforms the array weights of assets Y_i into numerical weights (Rumelhart et al. 1986). Fractal statistics can build portfolios and convert the weights of arrays to numerical values applied in portfolio selection, being able to build the fractal portfolio.

The theoretical and practical aspects of optimizing portfolios for investors are useful. The assets follow a fractal distribution overcoming traditional models where risk and return are fractals but examined inaccurately as real moments. The portfolios in fractal form balance better return and risk on a more efficient assessment. The fractal provides a closer-to-reality tool to analyze the peak-fat-tails extreme event characteristics on the markets. The uncertainty, the fat tails of higher possibility of extreme losses, make investor barriers necessary to protect from potential extended losses. The risks require a thorough examination of their asymmetry by peak-fat-tails and robust strategies (Rumelhart et al. 1986).

3. Leadership in Naval Tactical Supremacy

National sovereignty is supported by the Armed Forces throughout the cycle of geopolitical evolution. The Leadership operates in a dynamic environment of checks and balances arise of new contradictory of interests and must face every circumstance. Intelligent Decision Support Systems-IDSS are useful for Tactical Leadership on the field. Informatics, Engineering, Management, Decision Sciences offers specialized solutions for specific problems in the field: space/area surveillance, threat detection, categorization, solution selection, threat containment, escalation assessment, war plans, peace agreement.

Leadership must inspire, motivate, Christidis (2019), thus the margin of excellence in tactical management in naval operations is significant and can be optimized also by IDSS systems of multidimensional functionality. These IDSS are capable of combining the entire multitude of environmental information, evaluating, classifying threats or opportunities, and proposing forms of strategic and tactical solutions.

4. The Markets

Speculating investors make dynamic decisions on their positions considering the two pillars of the markets: risk-free bonds and treasury bills and risky stocks. Securities are traded by three styles of investors: (i) chartists, or noise traders; (ii) fundamentalists; and (iii) dragonslayers. The chartists/noise traders invest in social mimicking and price momentum. The fundamentalists are logical, risk-averse investors that maximize their expected utility on wealth in constant relative risk aversion (CRRA) utility. Dragonslayer investors seek to fight bubbles and bursts in risky securities Westphal and Sornette (2023). Westphal and Sornette (2020) introduced the dragon-riders who evolved into dragonslayers Westphal and Sornette (2023). Westphal and Sornette (2023) also showed that financial analysts detect possible bubbles, produce a set of risky securities, and sell the overpriced, contrary to market inflation. To fight bubbles and crashes, the model analyzes all the market metrics. Westphal and Sornette (2023) reports robust results with the risky dividend and riskless assets. In ordinary time intervals out of extreme events, dragon-riders are fundamentalists (Westphal and Sornette 2020).

Investors allocate their wealth among risky and risk-free assets. Risk-free treasury bills/bonds have a flexible supply, paying a fixed r_f; the risky security of price P_t in time t has an endogenous equilibrium of demand and supply Westphal and Sornette (2023), and if the year was profitable, it pays dividend d_t of discrete stochastic growth Westphal and Sornette (2020):

$$d_t = d_{t-1}(1 + r^d{}_t) \tag{20}$$

the growth rate is $r^d \sim N\left(r^d, \sigma_d^2\right)$, $u_t(\overset{iid}{\sim})N(0, 1)$, (Westphal and Sornette 2023):

$$r^d_{i,\,t} = r_d + \sigma_d u_t \tag{21}$$

The excess return is $r_{exc,i} = r_i - r_f$:

$$r_{exc,i} = r_{i,t} + \frac{d_{t-1}\left(1 + r_t^d\right)}{P_t} - r_f \tag{22}$$

Each of the three groups of investors has a distinct strategy; the (i) fundamentalists put a portion, x_t^f, of their wealth in risky stocks and the rest in bonds, maximizing *E(U)* in CRRA utility. They perform myopically, updating the investments on the new information of the risky stock and its dividend.

(ii) Chartists evaluate historical data, comparing them to the other chartists' opinions Westphal and Sornette (2020), Kaizoji et al. (2015). Thus, they invest in the risky securities or treasury bills/bonds, with the possibility of keeping the position or altering it.

(iii) Dragonslayers trade risky securities to predict bubbles and crashes. They make a $E(r_{exc,\,i})$, evaluating potential bubbles and expecting meltdowns. $E(r_{exc,\,i})$ maximizes $E(U)$ similar to fundamentalists. Further higher moments provide more details about the behavior of investors Loukeris et al. (2021), Loukeris and Eleftheriadis (2024), Loukeris et al. (2024):

$$v_\gamma = 1 - \varepsilon_\tau \tag{23}$$

$$r_p = \sum\nolimits_i x_i r_{exc,\,i_t^*} \tag{24}$$

where v_γ is security i's health (0 in bankruptcy, 1 healthy), ε_τ is the CI's judgment on security i (0 healthy, 1 distressed), r_{exc,i_t^*} is superior security i^*'s return on efficient frontier, x_i is the weights:

$$U_t(r_p) = \sum\nolimits_i U_t\left(r_{exc,\,i_t^*}\right) \tag{25}$$

priced in the partial utility of each investor by each selected stock i^* will be $U_t\left(r_{exc.i_t^*}\right)$.

5. Bubbles and Dragonslayers

A dragonslayer counts the excess return momentum y_t above the long return $\bar{r}$ in exponential moving average with memory parameter a (Westphal and Sornette 2023) in time $t-1$ after r_{t-1} is calculated. It also distributes the future investments to securities from $t-1$ to t, as noise traders use the price momentum H_t, the y_t is more sensitive to accelerations in price growth, thus dragonslayers have the probability that overvaluation will cause a burst using the logistic function Westphal and Sornette (2023):

$$\lambda_t = \frac{1}{\left(e^{\frac{-(|y_t| - l_y)}{\bar{x}}}\right)} \tag{26}$$

As the l_y threshold measures the overpricing, signaling the excessive value to the dragonslayer, s defines his confidence in the overpriced time window. A dragonslayer will invest in risky securities in case of verification of a small deviation of the return by the long-term growth to make a portfolio that will sell in the appropriate timing, opposing market exuberance. At the time that the difference between present growth and long-term growth surpasses the level of tolerance, the dragonslayer will close his positions. Thus the dragonslayer strategically places on the market, similar to the fundamentalists, maximizing $E(U)$ in the same risk aversion parameter (Westphal and Sornette 2023). The predictions of bubbles on the $E(r_{exc,i})$ and crashes of risky securities by the dragonslayer as a contrarian calibrates the markets. At $t-1$, the dragonslayer concludes the expectation on stock return as Westphal and Sornette (2023):

$$E^d_{r_t} = (1-\lambda_t)w_y y_t - \lambda\, sign(y_t) w_y l_y + \bar{r} \tag{27}$$

where w_y *is the* weight of the bubble diagnosis and sign(y_t) is the direction of the bubble. $E^d_{r_t}$ flows in a time window with a scale $\frac{1}{1-a}$ (Westphal and Sornette 2023).

6. Computational Intelligence

KYDON is supplied by the best classifier from the current research: (a) modulars and (b) support vector, achines with hybrids acting like dragonslayers,

6.1. Modulars

MDN feedforward nets (Figure 1) consist of certain versions of MLPs. MDNs process their input in parallel. in multiple MLPs, redistributing the outcomes and forming a set in the topology that supports function specialization in every sub-module. The topology and intermediate layers are predetermined. Out of the four modular topologies available in the current research, I selected the linear feedforward of no-bypass. In opposing MLPs, not all MDNs are fully interconnected among the layers, and lesser weights are necessary for a similar-sized network (neurons), boosting the learning in lesser training exemplars. It is not certain that each module will specialize learning in single parts of the data. The inputs consisted of 16 neurons, 4 upper neurons on the hidden layers, TanhAxon as the upper transfer function, lower neurons without GA, TanhAxon for the lower transfer, and the learning rule, which was the momentum of 0.1, step size, and a value of 0.7 in the momentums in the backpropagation learning rule, with 706 exemplars and 1 output. The correction term is defined by the learning rule in the supervised learning control of 1000 maximum epochs; the termination is on the minimum mean square error of 0.01 threshold; the minimum criterion was used with the best load in the test and batch learning Loukeris et al. (2024). If the cross-validation MSE starts to rise, the system network begins to overtrain. Thus, cross-validation is preferred for terminating learning and was implemented in 11 systems. Genetic algorithms Holland ([1975] 1992), were incorporated in hybrids of MDNs to define potential alternative optimal classifiers.

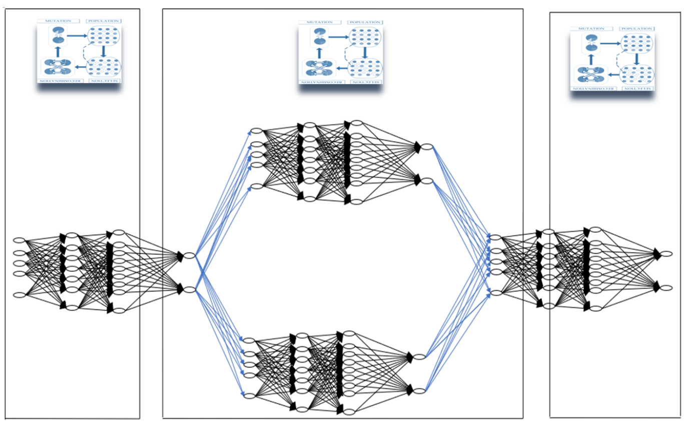

Figure 1. A hybrid modular network optimized with genetic algorithms and cross-validation in all the hidden layers.

6.2. Support Vector Machines

Support vector machines (SVMs) use categorically labeled training input data to create classification and regression binary entity outputs. The training of SVMs (Figure 2) is limited to sequential minimal optimization, as the output is unmarked and needs a slow training process in vast multiclass data. SVMs minimize their computing needs of multi-dimensional space through direct processing of inputs. On instances x_i, i = 1, . . ., l of y_i Є{1, −1} labels, SVM learning optimizes:

$$\min_{x} f(a) = \frac{a^T Q a - e^T a}{2} \tag{28}$$

$0 \leq \alpha_i \leq C$, i = 1, . . ., l, y^T α = 0

$$Q_{i,j} = y_i y_j K(x_i, x_j) \tag{29}$$

where e is a vector of all 1s, Q lxl is the symmetric matrix, $K(x_i, x_j)$ is the kernel function, and C is the upper bound of all variables. SVM rejects as overfitted any unstable patterns, offering statistically adequate resolution. The SVM used the Adatron kernel algorithm to map the inputs on a high-dimensional feature space. Then, the SVMs separated the data based on their classes, cutting off inputs close to the data limits. They learned by inputs close to the decision surface, using radial basis functions (RBFs), that attach Gaussians during backpropagation to every data sample to form the feature space of a dimensional degree equal to the number of samples. Adatron learning optimizes RBFs, replacing the kernel function with the inner product of patterns in the input space:

$$J(a) = \sum_{i=1}^{n} a_i - \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} a_i a_j d_i d_j \mathrm{G}(x_i - x_j, 2\sigma^2)}{2} \tag{30}$$

$$\sum_{i=1}^{n} d_i a_i = 0 \tag{31}$$

$\alpha_i \geq 0$, ∀i Є{1, . . ., N}

$$g(x_i) = d_i \left(\sum_{j=1}^{n} d_j a_j \mathrm{G}\left(x_i - x_j, 2\sigma^2\right) + b \right) \tag{32}$$

$$M = min_{j=1,\ldots n} g(x_i) \tag{33}$$

The 16 inputs are neutral to the SVM hybrids. The GAs Holland ([1975] 1992) were implemented in hybrids of (i) SVM inputs only, (ii) SVM outputs only, and (iii) both inputs and outputs. The weights used batch learning after the presentation of the whole training set. All models were tested on 500 and 1000 epochs, respectively, to optimize the iteration number upon convergence. The feature selection was performed either using the filter or the wrapper approach Westphal and Sornette (2020) independent of the learning algorithm. The bankruptcy prediction problem emphasizes the feature subset selection; its importance increases when the number of features is large, thus GA in the wrapper approach is used to select the optimal feature subset. The current research improves bankruptcy detection by SVMs. The increase function ends training with cross-validation if the MSE rises, avoiding overtraining, and the best training weights are loaded in the test set. Gas optimized the (a) number of neurons, (b) step size, and (c) momentum rate, with multiple training cycles to achieve the lowest error. Models with GA in the output layer optimized the step size and momentum. More epochs allowed for a thorough analysis of the iterations in them. Overall, the classifications of the SVMs excelled, with fine performance in the majority of parameters, but were exposed to overtraining in all different SVMs, revealing that the model is partial and dependent on the user. The hybrid SVM of 1000 epochs of GA optimization on the inputs and cross-validation converged optimally in classification and performance terms but under high overtraining exposure and a long computational time. The hybrid SVM of 500 epochs of GAs on the inputs had identical outcomes in a shorter time. The third rank is given to the SVM of 1000 epochs as very reliable but with the highest overfitting and very fast processing. These models are quite useful to all profiles of investors, putting emphasis either on accuracy or speed, whilst the overfitting aspect must be considered.

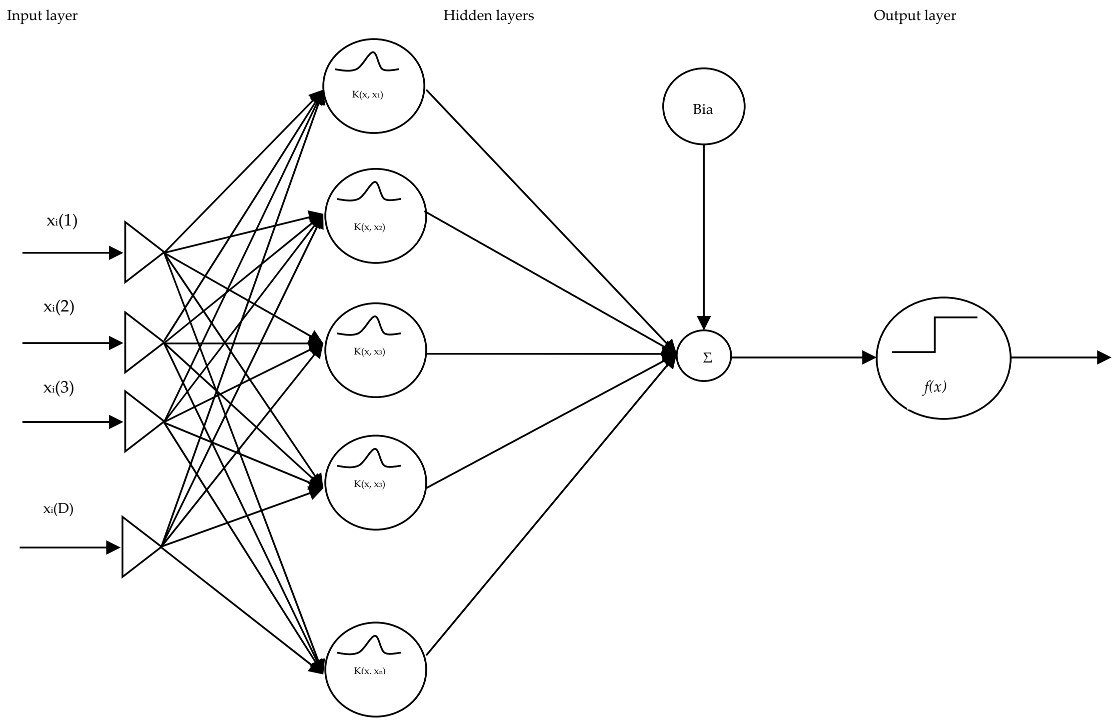

Figure 2. Support vector machines.

Although SVMs have superior classification and performance, they are exposed to partiality. On the other hand, MDNs had very good performance and classification, albeit slightly lower, they have high impartiality and are more reliable classifiers.

Support vector machines (SVMs) produce general regression and classification functions.

7. The Problem

Loukeris et al. (2021), Loukeris and Eleftheriadis (2024), Loukeris et al. (2024) reflect investor preferences, also extended on tactical leadership, in the problem:

$$U_t(R_t(i)) = \sum_{\lambda_\nu=1}^{\omega} \left(-1\right)^{\lambda_\nu+1} \frac{a_{\lambda_\nu}}{n} \sum_{i=1}^{n} \left(\frac{x_i - \sum \frac{x_i}{n}}{\sigma} \right)^n + \mathrm{Wx}(\mathrm{u},\mathrm{s}) \quad (34)$$

$$z = y^2 = \sigma^4 \quad (35)$$

The inductive logic of Aristotle and the Aponia-hedonism of Epicurus agree as to the core objective function of the model: the minimization of risk in all its detailed forms expressed in higher moments.

$$min_x f(x) = \lambda \upsilon_\gamma y \left[b + dz + ez^2 \right] \quad (36)$$

where υ_γ is the health of the asset (0 to bankruptcy, 1 healthy).

The non-convex surface of solutions needs robust computational resources for complex heuristics. Market manipulation increases risk. Risky securities in chaotic dynamics evolve in the stochastic differential equation (Shiller 2006):

$$dS(t) = S(t)\ [\mu\ dt + \sigma\ d(t) + J\ dN(t) - \lambda\ u\ dt] \tag{37}$$

where $J > -1$ is the jump amplitude of the stock, μ the mean return of the stock, σ the volatility without jumps, λudt *the* average growth of the Poisson jump, $u = E\ (J)$, $\{N(t), t \geq 0\}$ the Poisson of the λ strength, $\{W(t), t \geq 0\}$ the probability of a Brownian bridge (F, {F*t*} $t \geq 0$, P), $\{W\ (t)$ and $\{N(t)\ t$: non-negative} being independent between them, (Wang and Shang 2018), resolving SDE in (38):

$$\mathrm{S(t)} = \mathrm{S(0)}\prod\nolimits_{\mathrm{i=0}}^{\mathrm{N(t)}}(1 + \mathrm{J_i})e^{\mathrm{\mu t} - \frac{\sigma^2}{2}}\int_0^t P^{1-q}(\Omega, s)ds - \lambda ut + \sigma\Omega(t) \tag{38}$$

Ω(t), the random variable fulfills:

$$d\Omega(t) = P\ q(\Omega,\ t)^{(1-q)/2}dW(t) \tag{39}$$

as $Pq(\Omega, t)$ is the maximal entropy distribution of Tsallis in non-extensive statistics, representing volatility clusters in phenomena of long memory in stocks (Tsallis et al. 2003). The return r_i is:

$$\mathrm{r_{si}} = (\mathrm{S_t} - \mathrm{S_0})/\mathrm{S_0} \tag{40}$$

adjusting the excess return of the i optimal stock $r_{exc,si}$:

$$r_{exc,si} = r_{si} + \frac{d_{t-1}\left(1 + r_t^d\right)}{P_t} - r_f \tag{41}$$

Hence the utility is optimized by (Loukeris et al. 2024; Maringer and Parpas 2009) in

$$\text{Max } U_t(r_p) = \sum\nolimits_i U_t\left(r_{exc,\ i_t^*}\right) \tag{42}$$

or Loukeris et al. (2021), Loukeris and Eleftheriadis (2024), Loukeris et al. (2024), maintaining Epicurean hedonism in supperior risk details:

$$min_x f(x) = \lambda v_\gamma y_{exc,si}\left[b + dz_{exc,si} + e{z_{exc,si}}^2\right] \tag{43}$$

Intuitively, the triple-filtered market data (accounting, sentiments, chaos), adjusted to tactical capacity for the accounting part in case of naval leadership, are processed to provide the optimal portfolio with the highest financial wellfare, or tactical supremacy. The wealth alone is insufficient to describe the overall needs of each investor, who may have a serene profile (loss and risk averse), a neutral profile, or an aggressive, speculative profile. Similarly the efficient tactical balance need a wholistic support.

8. The KYDON

The risK-Yield Discriminant OptimizatioN—KYDON (Figure 3) at first obtains the prices, fundamentals, and the time horizon t, in case of naval leadership data from field and sensors, according to Policy, Objective. KYDON chooses the first classifier for assets, the λ of isoelastic utility, the risk of the investor (field commander). Next, it selects the evaluator classifier. Next, KYDON evaluates whether the best portfolio condition is met. It then receives the new data of the fundamentals and investor (personnel) sentiments on each stock Isi. If the new data on the securities changes to a higher value, then a local optimal portfolio (LOP) is created. If the LOP is approved, then it is withheld and KYDON ends; otherwise, it recalculates the portfolio on a new λ. Next, it reselects the classifier; otherwise, it proceeds creating two sets: A: for healthy firms (objective solutions) and B for distressed firms (field solutions). It calculates ε_τ (1: distressed or 0: fine firms). If $\varepsilon_\tau = 1$, the asset is removed; otherwise, if $\varepsilon_\tau = 0$, then the stock is fine and has the potential for an efficient Ut(Rt(i)) to be produced. Next, tests evaluate the ISi and $U_t(R_t(i))$, keeping the competitive assets. Next, securities are ranked by utility and then, KYDON creates an efficient frontier. Next, the assets of optimal utility enter the efficient portfolio, whilst a re-evaluation is performed on the subprimes. Other securities are re-evaluated for possible novel information. Next, the utility function $UP_j(f)$ is produced as is the efficient portfolio. The max utility $U^*P_j(f)$ overall portfolio is produced.

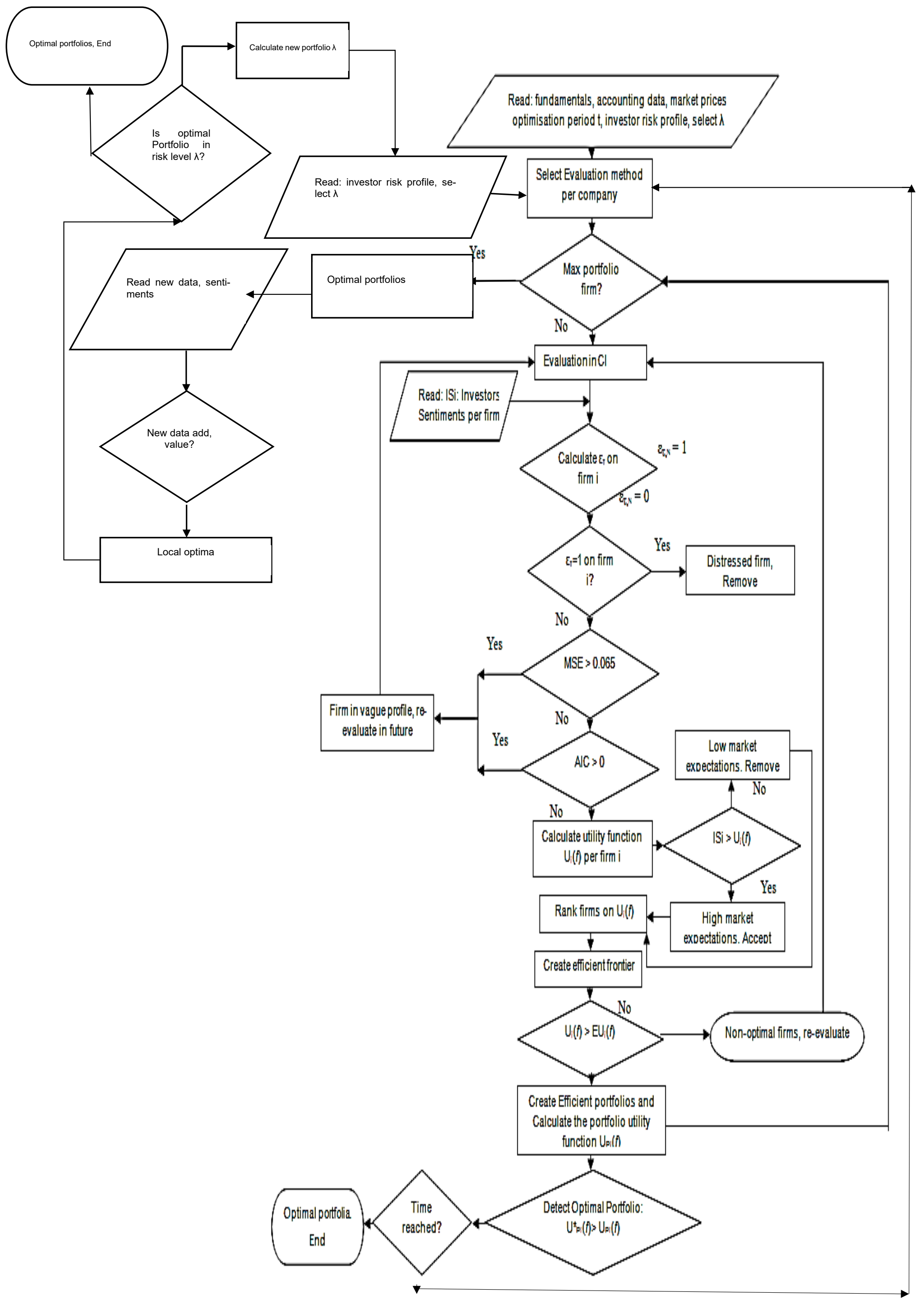

Figure 3. The KYDON.

KYDON acts as a dragonslayer trading risky securities to protect from crashes and bubbles. KYDON obtains the E(r_i) by examining the boom probability caused by fraudulent practices on the markets, preparing for meltdowns by filtering the long-term growth. E(r_i) optimizes the $E(U)$ like the fundamentalists.

9. DATA

The data was obtained from 1411 companies in a Greek bank. A total of 16 financial indices (Courtis 1978) were used: (1) EBIT/total assets, (2) net income/net worth, (3) sales/total assets, (4) gross profit/total assets, (5) net income/working capital, (6) net worth/total liabilities, (7) total liabilities/total assets, (8) long term liabilities/(long term liabilities + net worth), (9) quick assets/current liabilities, (10) (quick assets-inventories)/current liabilities, (11) floating assets/current liabilities, (12) current liabilities/net worth, (13) cash flow/total assets, (14) total liabilities/working capital, (15) working capital/total assets, (16) inventories/quick assets, while the extra seventeenth value classified the asset as the bankers defined it. The training set was composed of 50% of the data, whilst the test set was composed of the remaining 50%. Many different networks, plain or hybrid, on the MDN and SVM were used:

(i) MDN neural networks;
(ii) Hybrid MDN in genetic algorithms alone over the inputs layer;
(iii) Hybrid MDN in genetic algorithms on overall layers;
(iv) Hybrid MDN in genetic algorithms on overall layers with CV;
(v) SVM neural networks;
(vi) Hybrid SVM in genetic algorithms alone over the inputs layer;
(vii) Hybrid SVM in genetic algorithms on overall layers;
(viii) Hybrid SVM in genetic algorithms on overall layers with CV.

10. Results

The MDN systems had a more reliable overall efficiency (Table 1). The hybrid MDN in the GAs of two layers, with higher performance and classification, fitness of the model to the data, r, but high computing time, was the best MDN system.

Table 1. Optimal MDN and SVM models.

Models		Active Confusion Matrix				Performance						Time
	Layers	**0 → 0**	**0 → 1**	**1 → 0**	**1 → 1**	**MSE**	**NMSE**	**r**	**% error**	**AIC**	**MDL**	
MDN GA All	2	97.56	2.43	18.80	81.19	0.12	0.29	0.96	7.26	−533.73	71.40	18 h 29′29″
MDN GA All. CV	3	97.98	2.01	23.84	76.14	0.15	0.35	0.92	7.55	537.19	1749.41	15 h 16′39″
C.V.		98.07	1.92	25.04	74.94	0.14	0.33	0.91	9.09	511.92	1724.54	
SVM *500 epochs*		100	0	0	100	0.03	0.07	0.99	5.43	23,073.68	39,305.4	1′52″
SVM *1000 epochs*		100	0	0	100	0.03	0.06	0.99	4.85	23,016.76	39,248.5	4′11″
Hyb. SVM 500 ep GA in		100	0	0	100	0.04	0.08	0.99	6.55	16,159.80	27,896.0	14 h 39′31″
Hyb. SVM 500 ep GA out		100	0	0	100	0.06	0.12	0.99	6.80	23,457.92	39,689.6	1 h 07′34″
H. SVM 1000 ep. GA out		100	0	0	100	0.04	0.09	0.99	6.23	23,253.32	39,485.0	4 h 23′35″
H. SVM 500 ep GA in CV		100	0	0	100	0.02	0.04	0.99	4.01	12,044.20	21,524.3	26 h 56′14″
C.V.		94.29	5.69	22.01	77.98	0.30	0.59	0.94	12.72	13,931.09	23,409.9	
H.SVM 1000 e GA out CV		100	0	0	100	0.09	0.50	0.99	6.134	23,292.73	39,540.5	5 h 38′12″
C.V.		94.63	5.36	24.31	75.68	0.52	0.67	0.97	1.71	24,663.75	40,911.5	
H.SVM 500 ep GA All CV		100	0	0	100	0.09	0.17	0.99	9.06	12,375.85	21,401.5	21 h 16′32″
C.V.		95.88	4.10	25.22	74.76	0.54	1.03	0.98	25.12	13,646.24	22,672.4	

The second rank was given to the hybrid MDN of three hidden layers, cross-validation, adequate classification errors, good performance, and higher partiality, on a significant computational time. Although the SVMs had superior overall results, they showed very high partiality and thus cannot be considered robust and reliable classifiers. Their better classification and performance were neutralized by the very high values of partiality, and thus they are exposed to overfitting in lower reliability classifiers for this numerical financial problem. Thus, the third place is given to the SVM of 500 epochs optimized by GAs on the inputs only and cross-validation, in a 100% classification of the correctly classified assets, a fitness of the model to the data, r, of 0.999, the lowest error in MSE of 0.023, an NMSE of 0.045, an overall error of 4.01%, but a significant partiality of Akaike of 12,044.20, and an extended training time of 26 h 56 min 14 s. The processing time is not an issue for the trained model, as the cross-validation reduces overfitting. The main vulnerability of partiality shows dependence of its performance on the desired classification as given by human experts. But this is of lower significance, as the CV set was quite good, with 94.29% correct classifications in regard to healthy companies and 77.98% in regard to distressed companies, with a medium error of 0.309 in MSE, 0.591 in NMSE, and 12.72% in overall error.

Hence, the hybrid MDN with GAs of two layers is an efficient classifier on the KYDON to optimize portfolio selection and maximize the expected prosperity of the investor in terms of wealth according to his personal profile.

Time is not an important parameter to a trained network. The initial phase of training and testing may take some time as described, but after that, the processing is sharper. Obviously, the networks should be retrained and tested after some time to refresh their impact with the market data.

11. Concluding Remarks

The optimal classifier that fitted most sufficiently to the KYDON model in portfolio optimization is the Hybrid Modular Network-MDN with GAs and two hidden layers. The investors are protected in a triple filter: (i) fundamentals, (ii) chaotic patterns, (iii) sentiments that is applied overall the semi-strong efficiency set of information, and legally extended to the internal data through analytical processing of the hidden information. In the naval leadership, the fundamentals are consisted of the tactical and sensors data of the field. Thus, the excellent portfolio is given per investor and per optimal financial welfare. The welfare is holistic and includes the wealth, the balance, and the serenity. On the naval supremacy it is per field leader and per optimal tactical outcome.

The KYDON holistic system performs as a dragonslayer in portfolio optimization, as it trades assets of non-productive risk to protect bubbles and bursts. The KYDON through its optimal Hybrid Modular Network, makes a diagnosis on the extreme events (manipulation, fraud, hoax) that can magnify the bubble and protect from its drawdown as a crash.

For all $E(r_i)$, KYDON maximizes $E(U)$ as the fundamentalists have. Hence it manages optimally funds, investments, minimizing the idiosyncratic risk and warning about the systemic of that market. Additionally, in naval leadership it provides minimal risk exposure to field threats.

The Hybrid Modular GA-Network of 2 layers is a superior classifier but of lengthy processing that restricts real-time trading. Equivalently the Hybrid Modular GA-Network of 3 layers has similar classification quality. The future research will investigate methods of optimal analytical efficiency on the fractal n-dimensional space-time of information.

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