Portfolio Selection in Efficient Hybrid Modular, and Self Organised Features Maps Networks

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The Modular Networks and their Neuro-Genetic Hybrids are examined to address multiple aspects of the modern portfolio theory:

i) the investor behavior,

ii) the incorporation of the behavior to the stochastic differential equations to describe the price efficiently under the new trends of Chaotic Dynamics described by Tsallis Statistics on entropy in the frame of Fractal Market Hypothesis,

iii) the selection of the optimal classifier between 40 Modular models of plain and hybrid form to optimize investment portfolia.

The second phase process of portfolio selection advanced to detailed aspects of risk in further higher moments (volatility, hyperkurtosis, ultrakurtosis, hyperultrakurtosis, etc), Loukeris and Eleftheriadis (2017) is developed in this paper.

On the first step portfolios are evaluated, forming a feasible set, and secondly the ranked efficient portfolios minimize the risk on a utility function, Loukeris and Eleftheriadis (2020, 2019, 2017, 2016, 2015, 2014, 2012), Loukeris et al. (2009), Loukeris (2006, 2008).

This paper evaluates the first step which offers the solution to the second step.

44 Modular (MDN) & 44 Self Organised Features Maps (SOFM) models are evaluated in neural or neuro-genetic hybrids in

11 Modular & 11 SOFM neural and

33 Modular & 33 SOFM hybrids, in different topologies that detect the optimal classifier model of portfolio allocation.

This research:

Examines the preferences and the behavior of investors in advanced moments, on profits and risk exposure,

Extends the isoelastic utility as an advantageous tool,

Develops Markowitz's portfolio theory, with hidden information of fundamentals, to exclude the bias, and detect healthy assets, in the Fractal Market Hypothesis and Chaos Dynamics in Finance

Examines the efficiency of MDNs in neural or hybrid networks concluding on the optimal classifier for high frequencies trading

BEHAVIOR OF INVESTORS

Higher moments describe the investors hidden patterns on the implied utility function of the HARA (Hyperbolic Absolute Risk Aversion), thus advanced moments further than the 5th of hyperskewness are used Loukeris and Eleftheriadis, (2015b), Loukeris, Bekiros, and Eleftheriadis, (2016), Loukeris, Bekiros and Eleftheriadis (2016), Loukeris, Eleftheriadis, (2017)

$$U_t(R_{t+1}) = \sum_{\lambda_\nu=1}^{\omega} (-1)^{\lambda_\nu+1} \frac{a_{\lambda_\nu}}{n} \sum_{i=1}^{n} \left(x_i - \sum \frac{x_i}{n} \right)^n \quad (1)$$

where λ_v is the accuracy on investors preferences to risk, depending on the behavior, $a_{\lambda\nu}$ a constant on investors profile:

$a_{\lambda\nu} = 1$ for rational risk averse individuals, $a_{\lambda\nu} \neq 1$ for the non-rational, xi the value of return i in time t.

The Isoelastic Utility, a unique HARA function of Constant Relative Risk Aversion, is for the risk averse investors:

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

where, W the wealth, λ a measure of risk aversion. Loukeris, Eleftheriadis & Livanis (2014a), Loukeris, Eleftheriadis and Livanis (2014b), indicated the Makowitz model can have a broader alternative relaxing its essential assumption on the normally distributed prices.

THE MODEL

Loukeris, Eleftheriadis&Livanis (2014a), Loukeris,Eleftheriadis and Livanis (2014b) showed that further higher moments are necessary to describe the behavior of investors:

$$\min_x f(x) = \lambda \upsilon_\gamma \left[bVar_t(r_p) + d\, Kurt_t(r_p) + f\, HypKurt_t(r_p) - hUltraKurt_t(r_p) \right])] -$$
$$(1-\lambda)\upsilon_\gamma \left[aE_t\left(r_p\right) + cSkew_t\left(r_p\right) + eHypSkew_t(r_p) + \mathrm{g}\, UltraSkew_t(r_p) \right] \qquad (8)$$

$$\upsilon_\gamma = 1 - \varepsilon_\tau \qquad (9)$$

$$r_p = \sum_i x_i r_i^* \qquad (10)$$

where υ_γ company's financial health (0 to bankruptcy, 1 healthy), ε_τ the heuristic output as the evaluation result (binary: 0 healthy, 1distressed), r_i^* the return of stock *i* from the efficient frontier and is superior than the others, x_i their weights.

THE MODULAR NETWORKS AND THEIR HYBRIDS

The Modular feedforward networks are a special class of MLP.

These networks process their input using several parallel MLPs, and then recombine the results.

This tends to create some structure within the topology, which will foster specialization of function in each sub-module.

In the models the number of hidden layers, and the network topology can be defined.

There are four modular topologies supported, and in all the models is applied the linear feedforward form without bypasses of the signals.

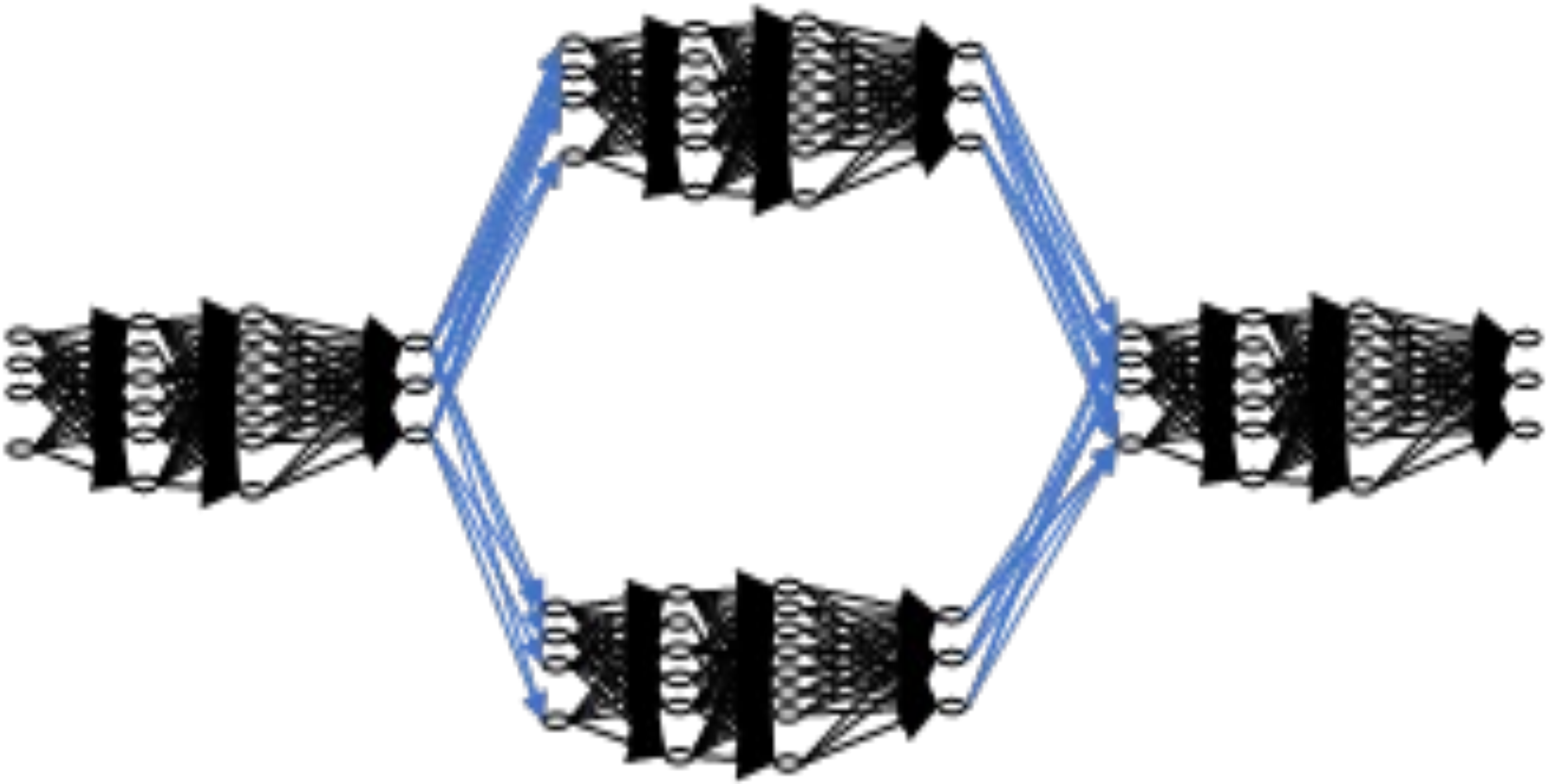

Fig. 1. The Modular Neural Networks

The Cross validation is a highly recommended method for stopping network training and it is used in 11 similar hybrid models.

It monitors the error on an independent set of data and stops training when this error is starting to increase, offering the best point of generalization to the calculations.

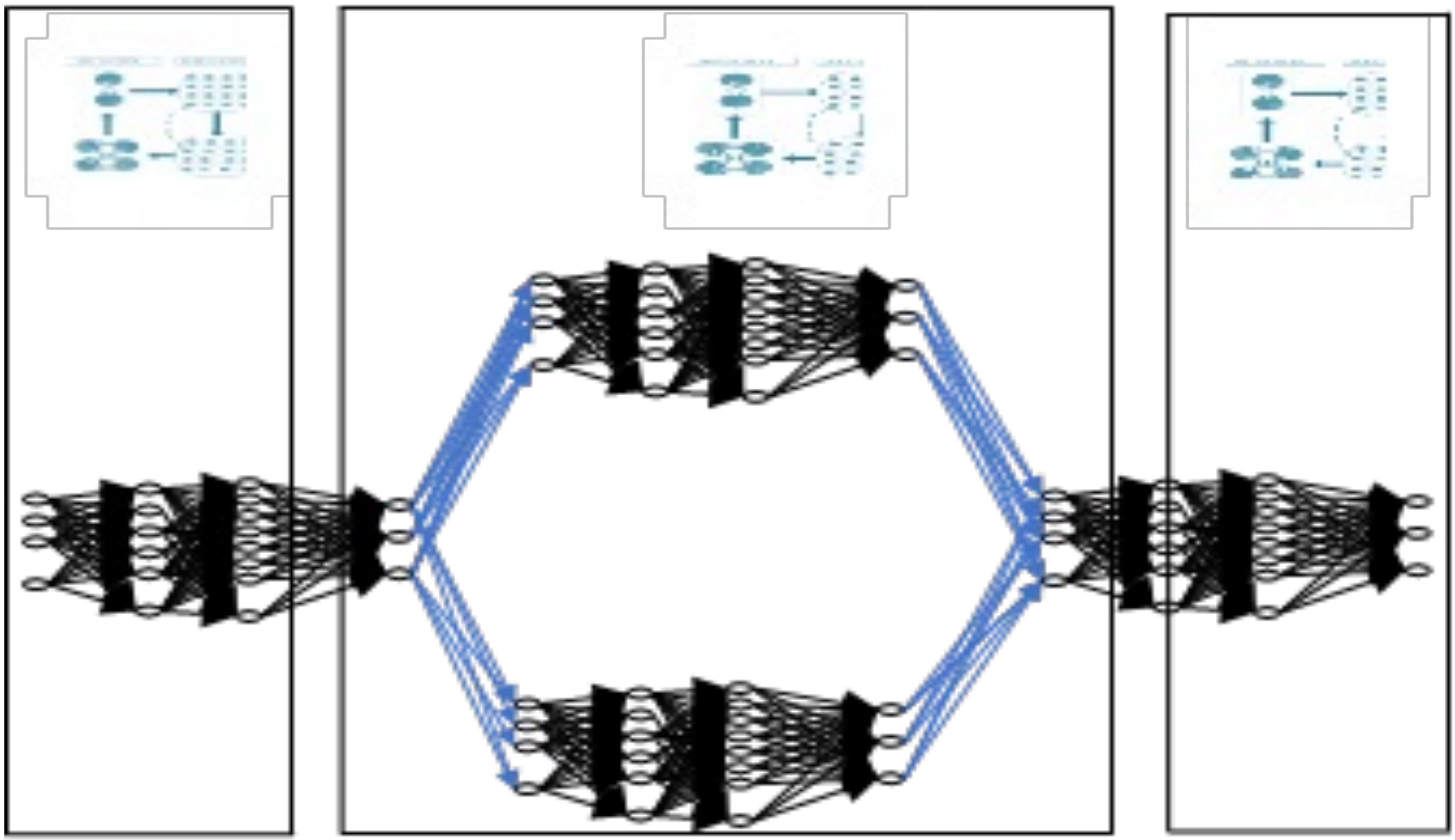

Fig. 2. The Hybrid Modular Net of GA optimization and Cross Validation in all the layers,

Self Organized Features Maps

Self Organized Features Maps-SOFM neural net, Kohonen (1982), optimises clustering & data examination

The SOFM learning is unsupervised creating a 2-dimensional map, (input surface) discretised on training data that minimise the dimensionality.

The SOFMs implement competitive learning, in contrast to the other neural nets.

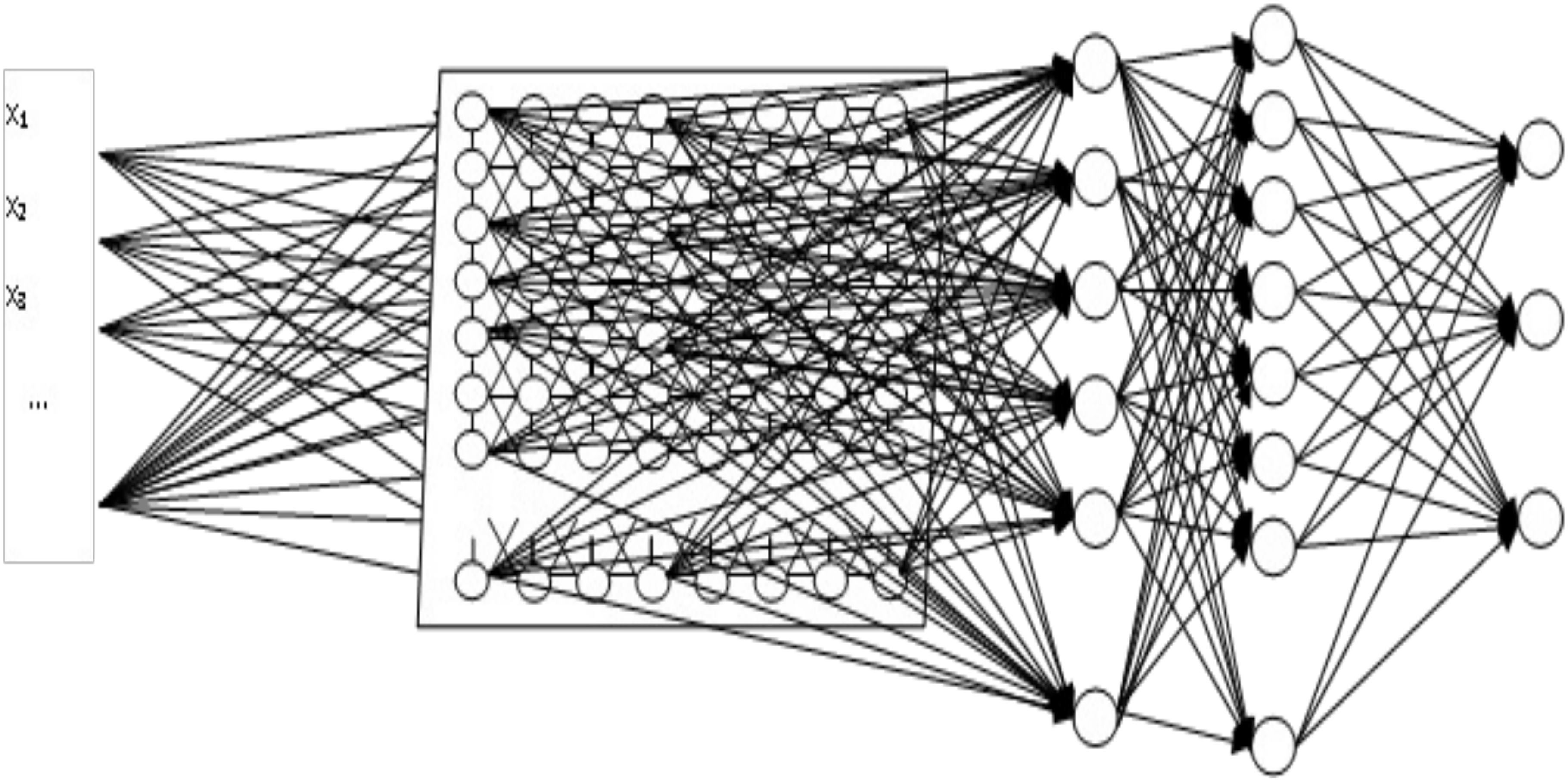

Fig. 3. Self Organized Feature Maps , Loukeris,Chalamandaris Eleftheriadis (2019),

The inputs of 16 fundamental indices have an unknown impact in SOFMs, thus we incorporate Genetic Algorithms-GA, Holland (1975/1992), to define it.

The models are trained under numerous repetitions to conclude the level of lowest error.

The GAs are used in different hybrids both for the MDNs and SOFMs of the inputs layer only, in different topologies.

The Batch learning adjusts the weights of MDN & SOFM.

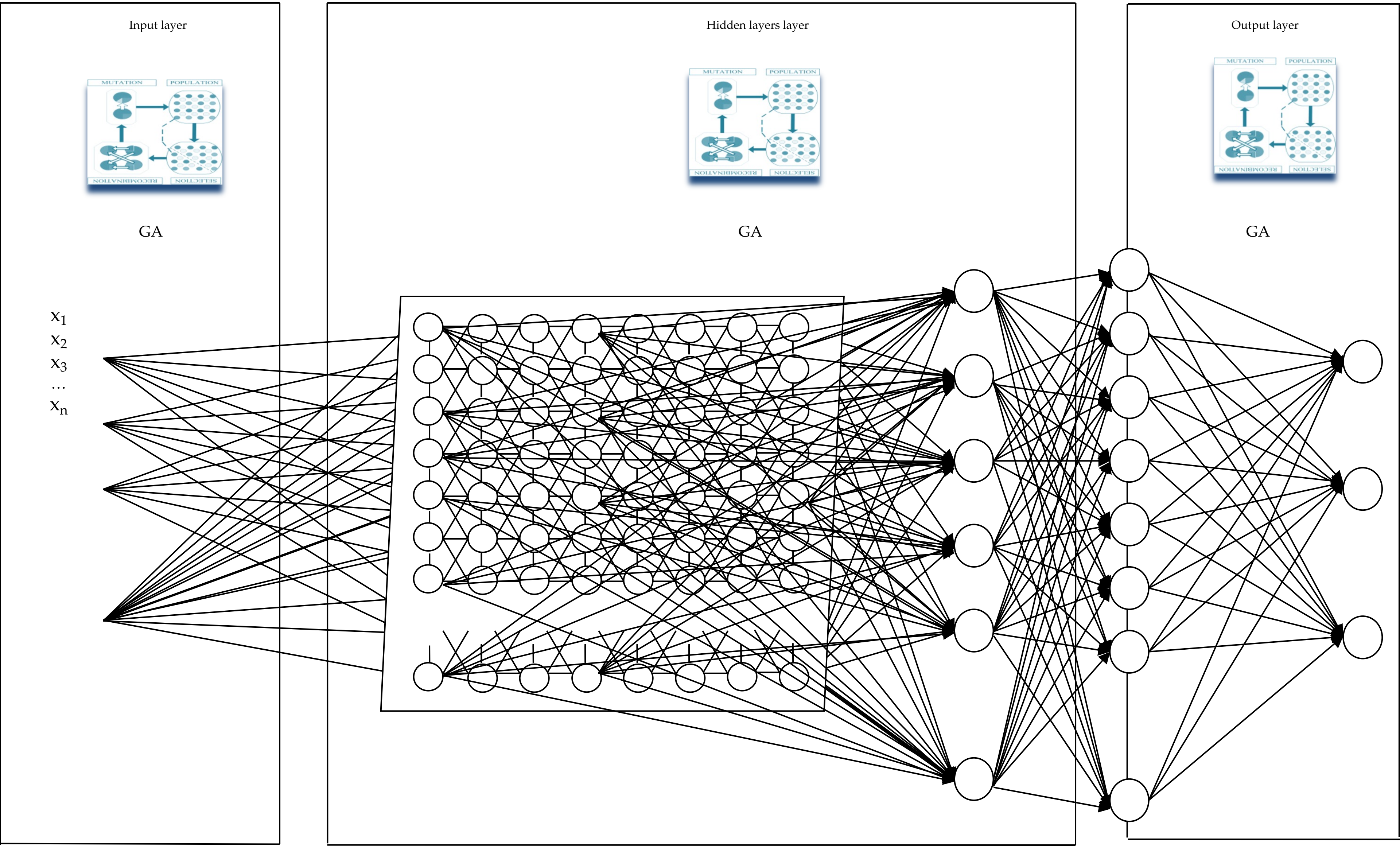

Fig. 3. Hybrid Self Organized Feature Maps with Genetic optimization on all layers & Cross Validation, Loukeris,Chalamandaris Eleftheriadis (2019),

The Batch learning was selected to update the weights of hybrid neuro-genetic models after the presentation of the entire training set.

The GAs also resolved the problem of optimal values in all the hidden layers and output in:

a) the Step Size and

b) the Momentum Rate.

PROBLEM DEFINITION

Maringer and Parpas (2009), Loukeris, Eleftheriadis (2017), Loukeris, Eleftheriadis and Livanis (2014a), Loukeris, Eleftheriadis and Livanis (2014b), indicated the necessity of further higher moments into the model, to optimally describe investors' preferences:

$$\min_x f(x) = \lambda \upsilon_\gamma \left[bVar_t(r_p) + d\,Kurt_t(r_p) + f\,HypKurt_t(r_p) - hUltraKurt_t(r_p) \right])] - (1-\lambda)\upsilon_\gamma \left[aE_t\left(r_p\right) + cSkew_t\left(r_p\right) + eHypSkew_t(r_p) + \mathrm{g}\,UltraSkew_t(r_p) \right] \quad (5)$$

$$\upsilon_\gamma = 1 - \varepsilon_\tau \quad (6)$$

$$r_p = \sum_i x_i r_i^* \quad (7)$$

where υ_γ the financial health of the company (0 bankruptcy, 1 healthy), ε_τ the heuristic evaluation result (0 healthy, 1distressed), r_i^* return of stock I in efficient frontier superior to other, x_i weights.

Problem Definition

The significance of further higher moments in the model was revealed by Maringer and Parpas (2009), Loukeris, Eleftheriadis, (2017), Loukeris, Eleftheriadis & Livanis (2014a), Loukeris, Eleftheriadis & Livanis (2014b) that provide a more realistic representation of preferences and thus the dynamic behavior of investors.

Loukeris, Eleftheriadis, (2017) introduced the form of the problem as:

$$U_t(R_t(i)) = \sum_{\lambda_v=1}^{\omega} (-1)^{\lambda_v+1} \frac{a_{\lambda_v}}{n} \sum_{i=1}^{n} \left(x_i - \sum \frac{x_i}{n} \right)^n + \mathrm{W_x(u,s)} \qquad (12)$$

The non-convex form of the problem demands robust heuristics for the solution.

Rumors, manipulation, cooked accounting have higher levels of risk

In terms of the Chaotic Dynamics the Risky stock prices follow the Stochastic Differential Equation, Biro & Rosenfeld (2012):

$$dS(t) = S(t)(\mu dt + \sigma\, d(t) + JdN(t) - \lambda udt) \quad (17)$$

where μ expected return of the stock, σ volatility without jumps, J a random variable of the jump amplitude within the stock ($J > -1$).

$u = E\,(J)$ an expectation operator, $\{N(t)\ ,t \geq 0\}$ a Poisson process with strength λ, λudt an average growth by the Poisson jump, $\{W(t),\ t \geq 0\}$ a standard Brownian motion defined on probability (F, $\{Ft\}$ $t \geq 0$, P), $\{N(t)\ ,\ t \geq 0\}$ and $\{W\,(t)\ ,\ t \geq 0\ \}$ are independent of each other, Biro & Rosenfeld (2012).

The SDE (17) solution is Zhao, Pan, Yue & Zhang (2021):

$$S(t) = S(0)\prod_{i=0}^{N(t)}(1 + J_i)e^{\mu t - \frac{\sigma^2}{2}\int_0^t P^{1-q}(\Omega, s)ds - \lambda u t + \sigma\Omega(t)} \quad (18)$$

The random variable Ω(t) satisfies:

$$d\Omega(t) = Pq(\Omega,t)^{(1-q)/2} dW(t) \quad (19)$$

where $Pq(\Omega,t)$ the maximum Tsallis entropy distribution of Non-extensive statistics.

The model can describe the volatility clustering and long-term memory phenomena of asset prices Zhao, Pan, Yue & Zhang (2021).

DATA

Data were produced by 1411 companies from the loan department of a Greek commercial bank, in 16 financial indices:

1) EBIT/Total Assets, 2)Working Capital/Total Assets,

3) Gross Profit/Total Assets, 4) Net Income/Working Capital,

5)Net Worth/Total Liabilities, 6)Total Liabilities/Total assets,

7)Quick Assets/Current Liabilities, 8) Inventories/Quick Assets,

9)Long Term Liabilities/(Long Term Liabilities+Net Worth),

10)(Quick Assets-Inventories)/Current Liabilities,

11)Floating Assets/Current Liabilities, 12) Sales/Total Assets,

13)Current Liabilities/Net Worth, 14) Cash Flow/Total Assets,

15)Total Liabilities/Working Capital, 16) Net Income/Net Worth,

a 17th index of initial classification, by bank executives. Test set was 50%, and training set 50% of data.

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Concluding Remarks

The MDN hybrid networks of 2 hidden layers with GA in all layers had superior classification and performance in an extended processing time.

The MDN hybrids of 3 layers with GA in all layers and and Cross Validation, was ranked second in superior classification and performance at an elongated processing time.

The SOFMs underperformed characteristically, and their best model was the SOFM neural net of 7 layers with mediocre performance in a medium time of process.