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The Intelligent Portfolio Performance Optimization System (IPPOS)

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Abstract

The stock returns are vulnerable to manipulation of peculiar forms. We propose a novel method, the Intelligent Portfolio Performance Optimization System—IPPOS that extracts hidden patterns from the vast accounting data, financial statements, and other values, elaborating them on a new Jordan Elman hybrid network to provide safer financial evaluations. The free will problem is answered in the specialization of portfolio selection.

Keywords

Integrated Systems, Generalized Feedforward Networks,
Jordan & Elman Network, Genetic Algorithms, Finance,
Portfolio Optimization, Logic, Free Will, Eudaimonia, Epicurus, Aristotle

1. Introduction

The weak explanatory power of the Gaussian probability distributions on returns and quadratic investor preferences does not adequately support the Markowitz's mean-variance criterion under the von Neumann-Morgenstern axioms of choice, (Markowitz, 1991; Loukeris et al., 2009). The Power Utility demonstrated a marginal superiority on the Quadratic function, emphasizing skewness (Loukeris et al., 2009). As investors prefer positive skewness, to earn high profits from extreme events, Boyle & Ding (2005), low kurtosis in lower risk probability because of the extreme outcomes in both sides of the distribution (Athayde & Flores, 2003), Lai, Yu, & Wang (2006). Thus more accurate detection of preferences requires further higher moments, (Loukeris et al., 2014a; Loukeris & Eleftheriadis, 2012), that minimize the uncertainty of the information and thus false evaluation of stock prices either endogenous, or exogenous. Actually, the rational utility maximizers lack of descriptive accuracy as they theoretically define the investment behavior, failing to approach the real behavior (Subrahmanyam, 2007). Usual patterns such as overconfidence on private signals cause overreaction, such as the BE/ME effect, the long-run reversals, that cause momentum. The loss aversion (Barberis & Huang, 2001) is a robust cause for price fluctuations.

The prices deviate significantly from their fundamental values according to social mimicking, thus an arbitrage strategy can achieve profits combining contrarian and momentum trading, and as markets are inefficient, prices are very noisy (Barberis & Sheifer, 2003).

Whilst a strong trend of disposition, to sell winners too soon and hold on to losers too long, although past winners do better than losers, is observed (Shefrin & Statman, 1984a). Characteristics of gender such as the superiority of women's conservative tactic, the low frequency of trading, environmental, the good weather, or other non-rational parameters determine the quality of investments. Considering all these parameters we move forth to create an integrated model or portfolio selection, the IPPOS, elaborating models Hybrid neuro-genetic models from the Generalized FeedForward and the Jordan Elma family. The optimal selection problem within a portfolio follows a two-phase process. We investigate the first phase of the optimization problem. The single period model is evaluated, as we introduce six different Generalized FeedForward and Jordan Elman hybrid net models of 11 different topologies each and 4 hybrid forms with Genetic Algorithms, to calculate the efficient frontier surface, in a quintuple scope: i) To analytically investigate the behavior of investors in higher moments; ii) To introduce an advancement of the isoelastic utility; iii) To advance the Markowitz's portfolio theory, considering apart from in fundamentals evaluation, other available data; iv) To evaluate the performance of the Generalized FeedForward and the Jordan Elman networks in neuro-genetic hybrids or neural network in different topologies in a new learning process; v) To introduce the integrated model IPPOS in optimal portfolio selection problems.

This research in Section 2 provides description on the markets, the higher moments, the utility, the investment behavior, Section 3 describes the methodology. Section 4 describes the data. Section 5 includes the results and Section 6 the conclusions.

2. Is Free Will in the Investment Behavior?

The expected returns alter in the cross-section for multiple reasons, one of which is the risk differentials across stocks. We proceed on a further analysis of risk puts emphasis on the connection of loss to risk aversion in our model, considering also non-rational parameters such as, gender, time, firm's proximity to investor, etc, incorporating the non-linear effects. The loss-aversion and the non-linear constraints are examined into the integrated Intelligent Portfolio Performance Optimization System (IPPOS) we introduce.

The returns distributions are not n.i.i.d., although the Fractal Markets Hypothesis-FMH appears to be quite capable to describe the markets complexity. We model investment preferences including terms of non-linearity, and non-causality. Investors allocate their utility between fears and earnings. They seek a reasonable level of return, under the fear of loss, concluding on doubtful decisions. During bullish periods the fear of losing excess profits, whilst in bearish the fear of maximizing losses, increase non-rational herding reactions on markets. (Loukeris et al., 2014a, 2014b; Loukeris & Matsatsinis, 2006), (Loukeris et al., 2016b; Merton, 2009; Odean, 1998; Shefrin & Statman, 1984b) and (Loukeris et al., 2015a, 2015b) elaborated further higher moments on the utility function of the HARA family (Hyperbolic Absolute Risk Aversion). Based on the 5th of hyperskewness and the 6th of hyperkyrtosis moments (Loukeris, Bekiros, & Eleftheriadis, 2016a) as:

$$\begin{aligned} U_t\left(R_{t+1}\right) = aE_t\left(R_{t+1}\right) - bVar_t\left(R_{t+1}\right) + cSkew_t\left(R_{t+1}\right) - dKurt_t\left(R_{t+1}\right) \\ + eHypSkew_t\left(R_{t+1}\right) - f\,HypKurt_t\left(R_{t+1}\right) \end{aligned} \tag{1}$$

where

$$Kurt_t\left(R_{t+1}\right) = Var_t^2\left(R_{t+1}\right) \tag{2}$$

$$HypKurt_t\left(R_{t+1}\right) = Var_t^4\left(R_{t+1}\right) \tag{3}$$

$$Skew_t\left(R_{t+1}\right) = E\left(x_i - \mu\right)Var_t\left(R_{t+1}\right) \tag{4}$$

$$HypSkew_t\left(R_{t+1}\right) = E\left(x_i - \mu\right)Var_t^2\left(R_{t+1}\right) \tag{5}$$

The general form of the utility function is:

$$U_t\left(R_{t+1}\right) = \sum_{\lambda_v=1}^{\omega}\left(-1\right)^{\lambda_v+1}\frac{a_{\lambda_v}}{n}\sum_{i=1}^{n}\left(r_i - \mu\right)^n \tag{6}$$

where λ_v is the depth of accuracy on investors utility preferences to risk, a_{λ_v} a constant on investors profile: $a_{\lambda_v} = 1$ for rational risk averse individuals that follow linear reasoning models with accepted causality levels, $a_{\lambda_v} \neq 1$ for the non-rational, x_i the value of return i in time t.

The Isoelastic Utility, a CRRA function is on the risk averse investors:

$$U\left(w\right) = \begin{cases} \dfrac{W^{1-\lambda} - 1}{1-\lambda}, & \lambda \in \left(0,1\right) \cup \left(1, +\infty\right] \\ \log\left(w\right), & \lambda = 1 \end{cases} \tag{7}$$

where, W the wealth, λ a measure of risk aversion.

The core problem of Philosophy on the Logic is a source of continuous discussion since the dawn of civilization. Common sense accepts our full responsibility of our choices, but are we? The freedom of selection comes from the freedom of will, in one perspective. But opposing this point many thinkers reject that our will can be managed freely. The Incopatibilists declare the irreconcilability of determinism to freedom, emphasizing in randomness that replaces determinism. Compatibilists support determinism and freedom is consistent. The Libertarians accept freedom, opposing Sceptics who believe the impossibility of freedom. (Loukeris & Eleftheriadis, 2024) noticed the agreement of Epicurus to Aristotle that happiness is the highest good, refusing to identify happiness with pleasure as: i) Subjects are only chasing pleasure, and Epicurean ethical hedonism emphasizes on psychological hedonism; ii) In accordance to the Epicurean empiricism, concludes on the introspective experience: (pleasure is desired and pain is avoided). Thus, Epicurus notices that all our actions maximize the gain of our pleasure. The free will approach, accepts the impossibility of our free will judgments as systematically false (Latham, 2019). (Colasante & Riccetti, 2021) remarked that the research stops to the fourth moment because behaviors at higher orders are often the same as making random choices, ignoring though that the patterns of the unconscious which produces random thinking, thus nature follows random patterns, fed to the subconscious and reflected to ego, altering logical thinking. Hence, higher-order moments reflect the detailed patterns of behavior in gain and loss of non-linearity to the limits of randomness. (Loukeris & Eleftheriadis, 2024) concluded that logic is dynamic in a linear process that adjusts to overriding new challenging ideas that offer higher potentials than the usual series of events. Its non-linearity is consistent to the maximization of utility and investors' financial welfare. Future work will examine in detail the numerical results of the utilities and wealth impact of the current models incorporating new trends that experience bubble effects.

3. Methodology

The convex problem of quadratic utility maximization (Markowitz, 1952), is improved by (Maringer & Parpas, 2009):

$$\min_x f(x) = \lambda Var(r_p) - (1-\lambda) E(r_p) \tag{8}$$

(Loukeris et al., 2014a, 2014b) and (Loukeris et al., 2015a, 2015b) emphasized on further higher moments in the model:

$$\begin{aligned} \min_x f(x) = {} & \lambda \upsilon_\gamma \left[bVar_t(r_p) + dKurt_t(r_p) + f\, HypKurt_t(r_p) \right] \\ & - (1-\lambda) \upsilon_\gamma \left[aE_t(r_p) + cSkew_t(r_p) + eHypSkew_t(r_p) \right] + s^{\log \lambda_v} \end{aligned} \tag{9}$$

$$\upsilon_\gamma = 1 - \varepsilon_\tau \tag{10}$$

$$r_p = \sum_i x_i r_i^* \tag{11}$$

where υ_γ the company's financial health, ε_τ the heuristic output (0 healthy, 1 distressed), s the social effect of non-rational features, as gender, local proximity, day of week, weather, frequency of trading, preference of on-line trading etc., r_i^* the return of stock i in the efficient. The stocks do not fulfill all the superiority conditions are non-optimal and are exempted from the efficient frontier. As

$$E\left(U_P(w,\lambda)\right) = \max \left\{ \sum_i \left[1 + \exp(r_i x_i) \right]^{1-\upsilon_\gamma/\lambda} \Big/ \left(1 - \upsilon_\gamma / \lambda \right) \right\} \Big/ N \tag{19}$$

let

$$Var_t^2(R_p) = z \tag{12}$$

$$Var_t(R_{t+1}) = y \tag{13}$$

as

$$z = y^2 = \sigma^4 \tag{14}$$

then

$$\begin{aligned}\min_x f(x) = {} & \lambda \upsilon_\gamma Var_t(R_p)\left[b + dz + fz^2\right] \\ & -(1-\lambda)\upsilon_\gamma\left[a\mu + cE(x_i - \mu)y + eE(x_i - \mu)y^2\right] + s^{\log \lambda_v}\end{aligned} \tag{15}$$

The novel contribution is that we extract hidden weighted social and financial patterns that can make the difference on the stock's evaluation. The frequency of turbulence in the markets is more compatible to the FMH, because of the extended amount of noise that causes chaotic patterns and the numerous manipulations attempts from other agents. The manipulation of stocks because of internal information is filtered. The evaluation υ_γ, in (10) is more important than the investor's behavior, because of the reverse influence in υ_γ/λ. The flow chart of processes is described in **Figure 1**. On the IPPOS the problem of portfolio optimization is extended to the principal philosophical remark on the Free Will expressed by investors selection.

4. The Intelligent Portfolio Performance Optimization System—IPPOS

The Intelligent Portfolio Performance Optimisation System -IPPOS on the first step reads the fundamentals, the accounting data, the market prices, the preferred optimisation period *t*, and the social sentiments of investors.

In parallel the social sentiments of investors are evaluated between them to define common patterns.

Then if there are common patterns the sentiments are compared to the stock price that are refereed to and are available, in time j during processing.

If they agree then the evaluation of data is preceded by hybrid models, else the sentiments are rejected and new data are examined starting the process from the first step.

Then it proceeds by selecting the initial method to evaluate the companies whose stocks are candidate in the portfolio. On this step the individual investor's risk profile is given and the λ is selected for the Isoelastic utility.

On the next step the system examines if this is the last firm to be examined, and if the condition for the optimal portfolio as an efficient portfolio is satisfied. Else we proceed on the next the initial evaluation uses a fast Neural Net that gives very accurate evaluations, and creates two subsets: Subset A of the healthy companies, and Subset B of the distressed firms. In the specific model we select the Jordan Elman Neural Net of 1 hidden layer that converges in 4 seconds only. The $\varepsilon_{\tau,N}$ value is calculated 0, for the healthy and 1 for the distressed firms. Both firms of subsets A, and B are re-evaluated in a double precision process, by a Hybrid neuro-genetic model of higher performance. Value $\varepsilon_{\tau,H}$ is calculated identically through the Hybrid net and it is compared to $\varepsilon_{\tau,N}$.

Next step these values are compared and if $\varepsilon_{\tau,N} = \varepsilon_{\tau,H}$ then the decision is final, else the firm is in vague profile and it is re-evaluated in future after more data are available, and cleared.

If $\varepsilon_{\tau,N} = \varepsilon_{\tau,H} = 1$ then the firm is a verified distressed firm and it is removed from the overall portfolio, else if $\varepsilon_{\tau,N} = \varepsilon_{\tau,H} = 0$ then it is a verified healthy firm and it is included on the Subset C of the healthy firms that are candidate for the optimal efficient portfolio.

On the next step the $U_t(R_t(i))$ utility function of (22) is calculated per firm.

Next firms are ranked according to their utility score.

Then the Efficient Frontier is calculated.

Next the firms with the higher utility score are selected into the efficient portfolio.

The sub-optimal firms as well as the non-optimal firms are revaluated with potential new data on the step 4 of Neural Nets evaluation, following all the steps.

Next after the efficient portfolio is created, its Utility Function is calculated $U_{Pj}(f)$.

Then the optimal overall portfolio $U^*_{Pj}(f)$ whose utility is the maximum available, is detected, if possible, by all the available efficient portfolios utilities

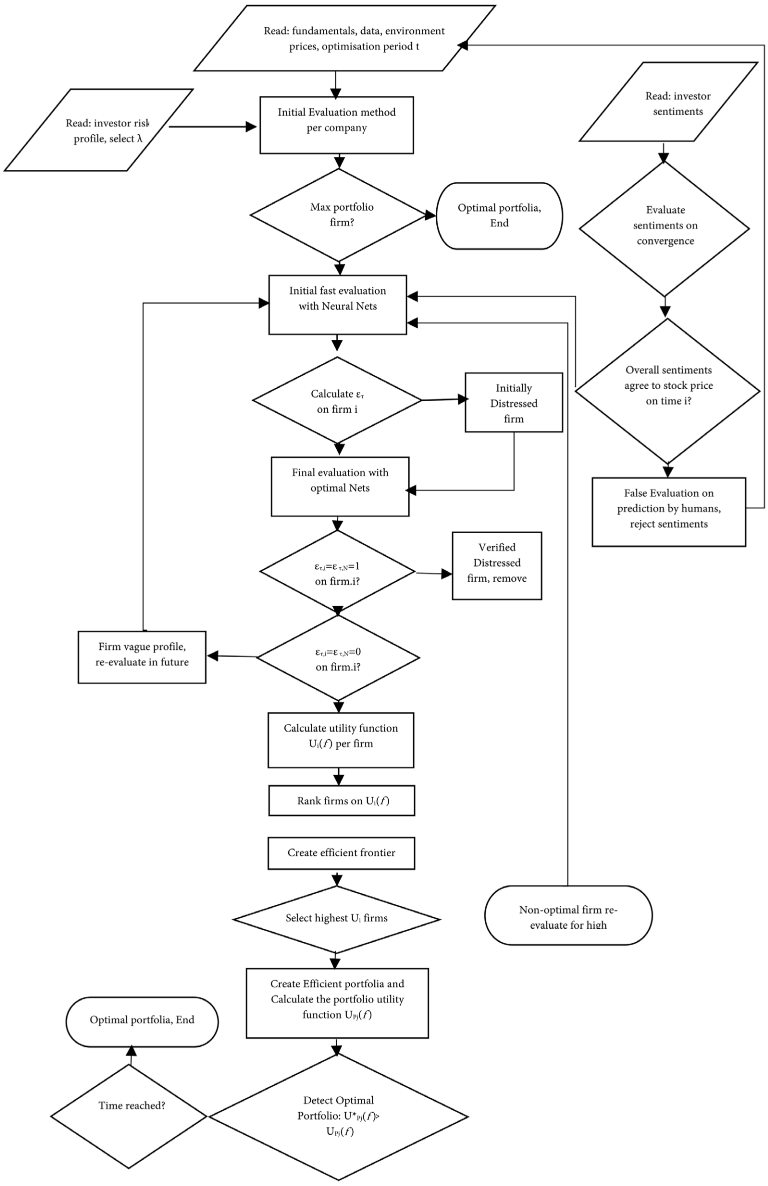

Figure 1. The IPPOS model.

$U_{Pj}(f)$ recorded in $U^*_{Pj}(f) > U_{Pj}(f)$.

The process stops when the time limit is reached and the IPPOS has the optimal portfolio.

The flow chart of the IPPOS is in above **Figure 1**.

5. The Initial Processing Phase

5.1 Partially Recurrent Neural Networks

The Partially Recurrent Networks are MLPs where few recurrent connections are created. The input layer of Partially Recurrent Networks includes the inputs, and the state neurons, that have memory on past actions and have outputs from one of the layers delayed by one step. Internal states, are a short-term memory (Galvan and Isasi, 2001). The Partial Recurrent Networks are i) the Jordan network, ii) the Elman network and iii) the Multi—Step Recurrent network.

5.1.1. The Jordan Network

The Jordan neural nets (Grinblatt & Han, 2005; Hong, Kubik, & Stein, 2005), include the context neurons that receive a copy from the output neurons and them (**Figure 2** & **Figure 3**).

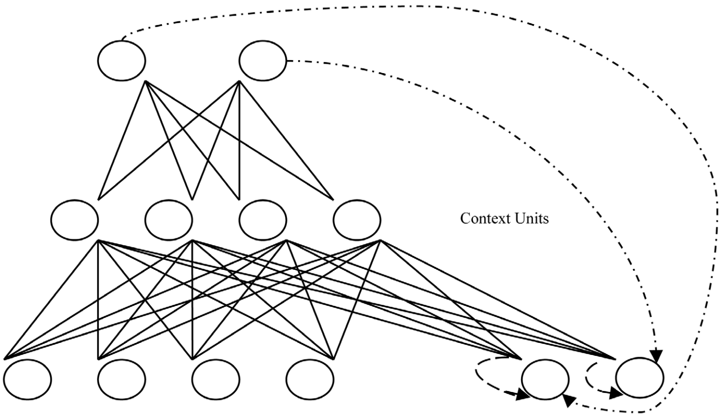

Figure 2. The single layer Jordan Network (Jordan, 1986a).

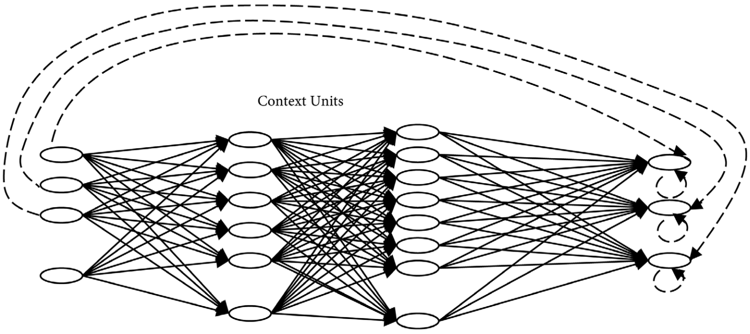

Figure 3. The Multilayer Jordan Net (Jordan, 1986b).

The recurrent connections from the output to the context neurons have an associated parameter of constant value: m ϵ (0, 1).

5.1.2. The Elman Network

The Elman networks (Elman, 1990) have the context neurons that receive a copy of the networks' hidden neurons and these connections do not need to associate any parameter. The number of the context neurons is the same to the number of hidden neurons into the network. The rest activations are calculated similarly as in the MLP (Stagge & Sendhoff, 1997) (**Figure 4** & **Figure 5**).

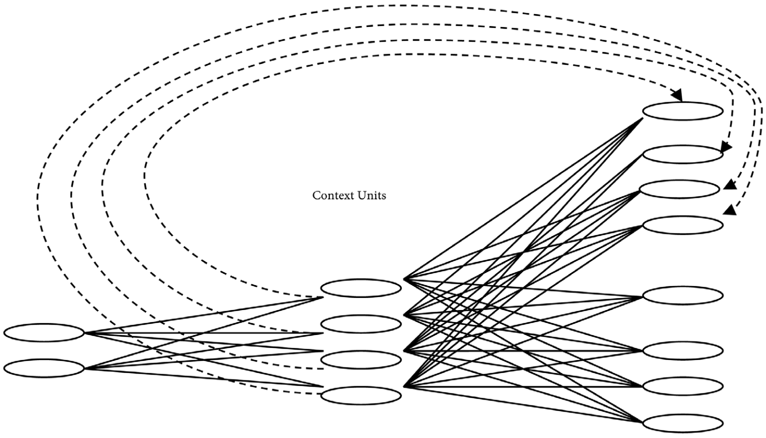

Figure 4. The single layer Elman Network (Elman, 1990).

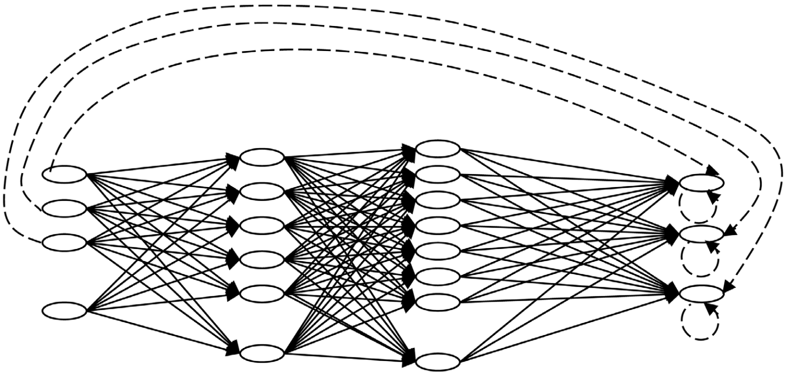

Figure 5. The Multilayer Elman Network (Elman, 1990).

5.1.3. The Multi-Step Recurrent Network

The Multi-Step recurrent network (Jordan, 1986a), has feedback connections directed from the output neuron to input layer. The context neurons memorise previous outputs of the network.

5.2. The Jordan Elman Networks

The Jordan and Elman (JE), nets extend the MLP in the context units' neurons that remember past activity. They offer the ability of extracting temporal information from the data. There are 4 topologies that feed the context units. Topology I provide the context units with the inputs, and builds a robust past substratum of the input by its memory traces. The topology II follows the Elman's method and builds memory traces from the initial layer. Topology III uses the past of the last hidden layer outputs as input to the context units. Topology IV uses Jordan's technique taking the past of the output to create the memory traces. We implement the topology I.

The significance on each one of the 16 financial inputs in all the JE nets is calculated through the Genetic Algorithms, on the Hybrid models only. These models are trained multiple times to detect the inputs combination that produces the lowest error. The GAs are elaborated in four different hybrid models of different topologies: i) On the inputs layer only; ii) On the inputs and outputs layers only; iii) Into all the layers; iv) Into all the layers with cross validation. The Batch learning was preferred to update the weights of hybrid neuro-genetic JE, after the presentation of the entire training set. The GAs also resolved the problem of optimal values in all the hidden layers and the output in: i) the Step Size and ii) the Momentum Rate. The JE nets require multiple training to achieve the lowest error (**Figure 6**).

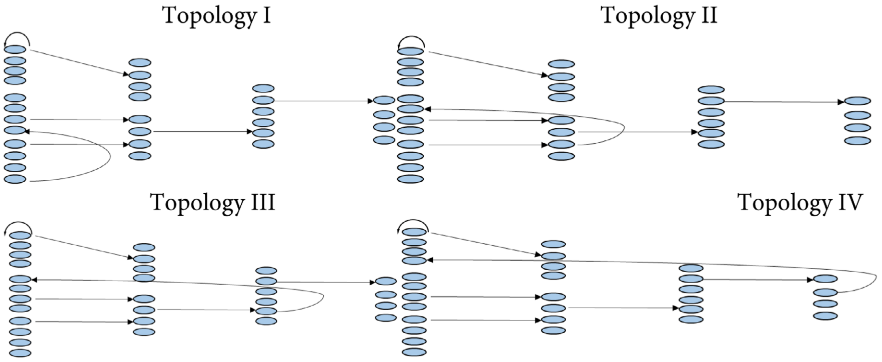

Figure 6. Processing in Jordan and Elman nets under the 4 different topologies.

5.3. The Generalized FeedForward Neural Networks

The Generalized FeedForward (GFF) neural networks are a generic form of the MLP who's the connections are able to jump over one or more of all the subsequent layers. The GFFs converge on the solutions much more efficiently than the ordinary MLP model (**Figure 7** & **Figure 8**).

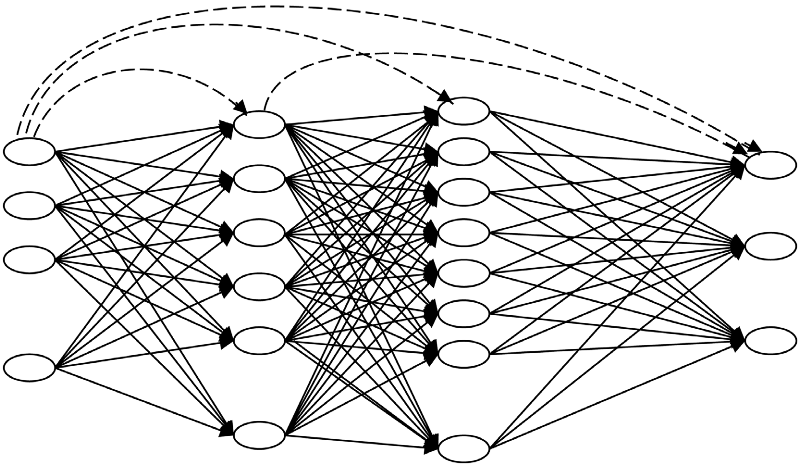

Figure 7. The generalized feed forward network.

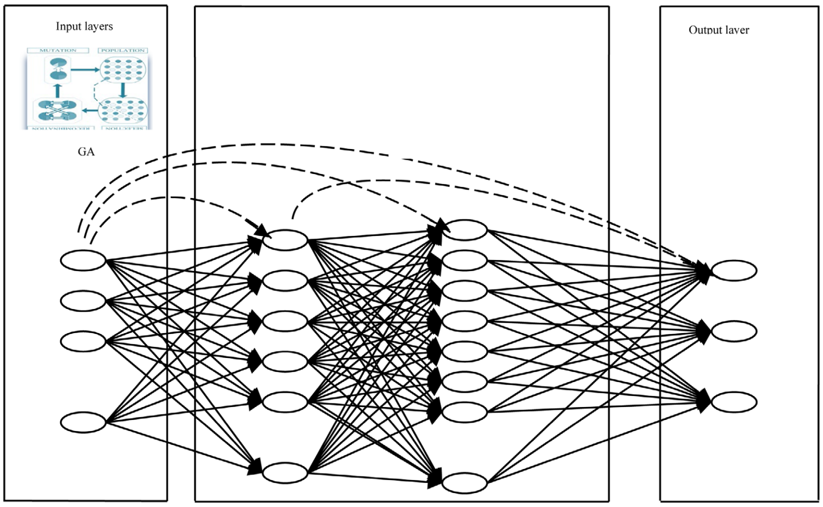

Figure 8. The Hybrid Generalized Feed Forward Net of GA optimization into the inputs only.

Usually the MLP requires hundreds of times more training epochs than the GFF neural network in the same number of neurons. Thus, GFFs are more attractive in complex problems of vast data and although Feedforward model it has the qualities of the Recurrent that can jump its synapses to neurons in other locations than the direct next layer. The importance of each one of the 16 financial inputs in the Generalized FeedForwards is calculated through the Genetic Algorithms, on the Hybrids. They are trained multiple times to detect the inputs of the lowest error. The Genetic Algorithms are elaborated in four different hybrid models of different topologies: i) On the inputs layer only; ii) On the inputs and outputs layers only; iii) Into all the layers; iv) Into all the layers with cross validation (Figure 9 & Figure 10).

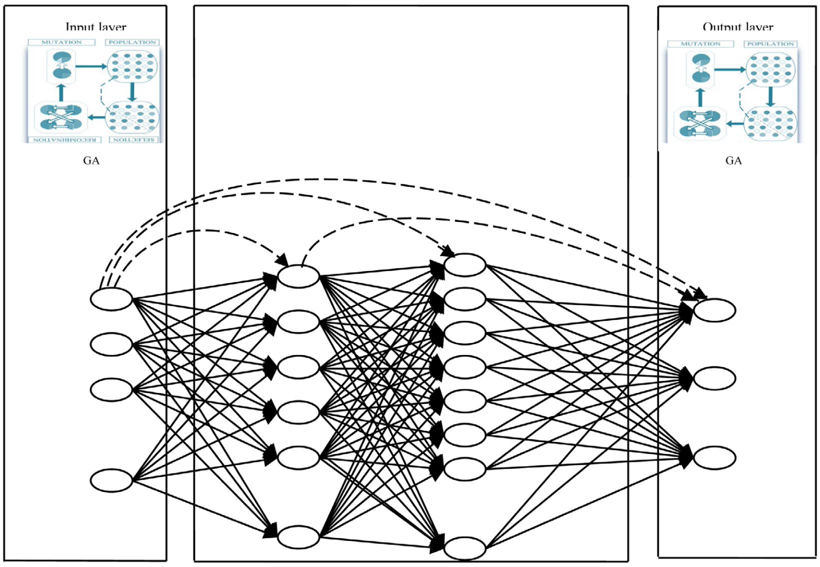

Figure 9. Hybrid Generalized Feed Forward Net of GA optimization in the inputs and outputs only.

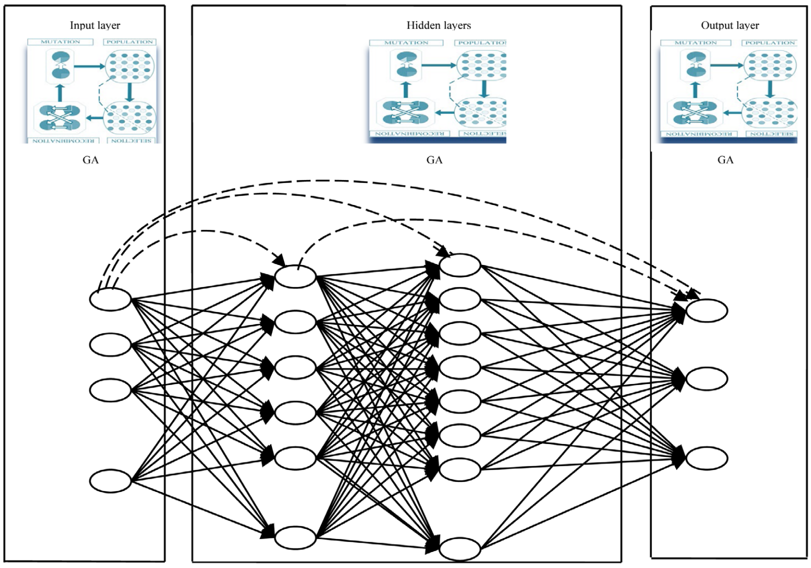

Figure 10. Hybrid Generalized Feed Forward Net of GA optimization and Cross Validation in all the layers.

The Batch learning updates the weights of the GFFs, after the presentation of the entire training set. The Genetic Algorithms solved the problem of optimal values in all the hidden layers and the output in: a) the Step Size and b) the Momentum Rate.

The GFFs require multiple training to achieve the lowest error. In numerous models the Cross Validation was used that monitors the error on an independent set of data and stops training when this error begins to increase. Thus, the status of best generalization is achieved.

5.4. Data

Data came by 1411 companies from the loan department of a Greek commercial bank, with the following 16 financial indices (Courtis, 1978):

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.

And a 17th index with initial classification, done by bank executives according to their calculations and the literature, which represents the desired outcome to which the Artificial Intelligence methods must converge, as this is a classification problem. Test set was 50% of overall data, and training set 50%. Multiple combinations were chosen to detect the performance of the GFF models:

i) GFF Neural Nets;

ii) GFF Neural Nets with Cross Validation;

iii) GFF Nets with GA in input layer only;

iv) GFF Nets with GA in input and output layers only;

v) GFF Nets with GA in all layers;

vi) GFF Nets with GA in all layers and Cross Validation.

Whilst for the JE networks we had:

vii) JE Neural Nets;

viii) JE Neural Nets with Cross Validation;

ix) JE Nets with GA in input layer only;

x) JE Nets with GA in input and output layers only;

xi) JE Nets with GA in all layers;

xii) JE Nets with GA in all layers and Cross Validation.

6. Results

The most optimal performance overall wass observed on the Jordan Elman Hybrid models of GA optimization on the input and outputs only of 1 layer where the healthy firms were correctly classified at 99.83% and the distressed at 96.78%, a very low error as MSE was 0.022, the NMSE at 0.052, and the error 3.83%, whilst the fitness of the data to the model was excellent as the correlations coefficient r was the highest 0.973, the model was also impartial as the Akaike was very low at −2481.73, and the processing time quite fast at 55 m. 18 s. The second place was taken by the JE Hybrid models of GA optimization on the input and outputs only no hidden layer with an excellent classification at 99.91% for the healthy companies and 96.78% for the distressed, the error was very low as well in 0.031 for the MSE, 0.075 for the NMSE, in an excellent of the data on the model as r was 0.978, and a great impartiality of AIC in −2416.06, in the fastest time of only 57 m. 29 s., but exposed to over-training phenomena. Similar performance on the third place had the JE hybrid with GA optimization in all layers and Cross Validation in an excellent classification outcome of 99.66% for the healthy, 94.49% for the distressed firms, a very low error as MSE was 0.023, NMSE 0.055, the overall error 12.32% in a very high fitness of the data to the model on r at 0.972, a great impartiality in Akaike at −2439.55, the Cross Validation performance was very similar to the model, whilst it protects from over-fitting hazard thus this model is the most appropriate for complex modelling, and a medium convergence time of 2 h. 35 m. 29 s., to the JE NN of 1 layer that is exposed to overtraining (**Tables 1-3**).

Table 1. Overall ranking of the optimal Generalized FeedForwards.

Active		Confusion Matrix				Performance						Time
	Layers	0→0	0→1	1→0	1→1	MSE	NMSE	r	%error	AIC	MDL	
GFF input-outp GA	*1*	*98.90*	*1.085*	*11.465*	*88.52*	*0.072*	*0.170*	*0.908*	*5.776*	*−1907.09*	*−1796.44*	*3 h 19’ 25”*
GFF GA all	3	97.14	2.845	17.885	82.10	0.128	0.304	0.834	8.343	40259.12	284.345	4 h 20’ 25”
	1	97.56	2.425	18.805	81.18	0.133	0.315	0.827	8.243	−723.47	−271.82	3 h 19’ 25’
GFF GA all,	7	96.64	3.35	19.26	80.73	0.136	0.323	0.825	9.119	1541.07	3429.31	25 h 46’ 34”
CV		98.32	1.67	29.355	70.63	0.149	0.353	0.812	7.073	1608.29	3495.49	
GFF NN	1	97.73	2.26	21.095	78.89	0.138	0.328	0.821	9.675	−1225.82	−1111.95	14”
GFF NN, CV	8	98.23	1.755	26.14	73.85	0.143	0.338	0.814	9.284	709.44	2041.35	1’ 03”
CV		98.23	1.755	26.14	73.85	0.143	0.338	0.814	9.284	709.44	2041.35	
GFF GA inputs	10	97.98	2.005	26.6	73.16	0.144	0.341	0.812	9.469	1219.39	2873.69	7 h 44’ 32”
GFF GA all	8	98.57	1.42	26.6	73.39	0.140	0.329	0.821	8.329	1262.65	2959.69	29 h 50’ 17”
GFF GA all,	1	97.98	2.005	24.30	75.68	0.145	0.343	0.810	8.646	−1219.07	−1126.3	2 h 27’ 41”

Table 2. Overall ranking of the optimal Jordan Elman models.

Active		Confusion Matrix				Performance						Time
	Layers	0→0	0→1	1→0	1→1	MSE	NMSE	r	%error	AIC	MDL	
JE input-output GA	*1*	*99.83*	*0.16*	*3.20*	*96.78*	*0.022*	*0.052*	*0.983*	*3836*	*−2481.7*	*−2355.07*	*55’ 18”*
JE input-output GA	0	99.91	0.08	3.66	96.32	0.031	0.075	0.978	4955.5	−2416.6	−2398.1	57’ 29”
Jordan Elman NN	1	99.91	0.08	3.20	96.78	0.022	0.053	0.972	37.603	−2407.8	−2212.1	4”
J Elman GA all,	2	99.66	0.33	5.50	94.49	0.023	0.055	0.972	1572.26	−2439.5	−2287.3	2 h 35’ 29”
CV		99.83	0.16	0.91	99.08	0.023	0.056	0.971	28.511	−2425.7	−2273.5	
J Elman GA all	1	99.83	0.16	5.50	94.49	0.026	0.062	0.970	4127.5	−2378.5	−2263.3	1 h 38’ 53”
J.Elman NN, CV	2	100	0	6.42	93.57	0.028	0.067	0.966	37.174	−2201.8	−1980.5	8”
CV		100	0	6.42	93.57	0.028	0.067	0.966	37.174	−2201.8	−1980.5	
J Elman GA inputs	1	100	0	8.25	91.74	0.027	0.065	0.966	40.46	−2352.8	−2226.1	20’ 01”
Jordan Elman NN	2	99.91	0.08	4.12	95.86	0.035	0.084	0.960	45.335	−2006.4	−1785.1	5”
J Elman GA inputs	2	99.83	0.16	7.33	92.66	0.039	0.092	0.956	47.15	−2006.0	−1824.9	54’ 24”

Table 3. Overall ranking of the optimal Jordan Elman and Generalized FeedForward models.

Active		Confusion Matrix				Performance						Time
	Layers	0→0	0→1	1→0	1→1	MSE	NMSE	r	%error	AIC	MDL	
Jor Elman in-out GA	*1*	*99.83*	*0.16*	*3.20*	*96.78*	*0.022*	*0.052*	*0.983*	*3836*	*−2481.7*	*−2355.07*	*55’ 18’*
Jor Elman inp-out GA	0	99.91	0.08	3.66	96.32	0.031	0.075	0.978	4955.5	−2416.6	−2398.1	57’ 29”
Jordan Elman NN	1	99.91	0.08	3.20	96.78	0.022	0.053	0.972	37.603	−2407.8	−2212.1	4”
Jor Elman GA all, CV	2	99.66	0.33	5.50	94.49	0.023	0.055	0.972	1572.26	−2439.5	−2287.3	2 h 35’ 29”
CV		99.83	0.16	0.91	99.08	0.023	0.056	0.971	28.511	−2425.7	−2273.5	

Continued

Jordan Elman GA all	1	99.83	0.16	5.50	94.49	0.026	0.062	0.970	4127.5	−2378.5	−2263.3	1 h 38’ 53”
Jord Elman NN, CV	2	100	0	6.42	93.57	0.028	0.067	0.966	37.174	−2201.8	−1980.5	8”
CV		100	0	6.42	93.57	0.028	0.067	0.966	37.174	−2201.8	−1980.5	
Jordan Elman GA inp	1	100	0	8.25	91.74	0.027	0.065	0.966	40.46	−2352.8	−2226.1	20’ 01”
Jordan Elman NN	2	99.91	0.08	4.12	95.86	0.035	0.084	0.960	45.335	−2006.4	−1785.1	5”
Jordan Elman GA inp	2	99.83	0.16	7.33	92.66	0.039	0.092	0.956	47.15	−2006.0	−1824.9	54’ 24”
MLP, GA all, CV	1	98.56	1.92	21.55	78.43	0.132	0.312	0.917	42.3573	−1305.0	−1224.4	2 h 20’ 08”
GFF input-outp GA	1	98.90	1.085	11.465	88.52	0.072	0.170	0.908	5.776	−1907.09	−1796.44	3 h 19’ 25”

The GFFs unfortunately had the worst outcomes overall. The best performance overall of the Generalised FeedForward networks was achieved on the GFF Hybrid with GAs on the inputs and outputs only of 1 layer where the healthy firms were correctly classified at 98.90% and the distressed at 88.52%, a very low error as MSE was 0.072, the NMSE at 0.172, and the error 5.67%, very high fitness of the data to the model as the correlations coefficient r was the highest 0.907, the model was also impartial as the Akaike was very low at −1808.33, and the processing time quite fast at 3 h 55 min. 18 s.

7. Conclusion

The integrated Intelligent Portfolio Performance Optimisation System-IPPOS provides robust approach into the real time portfolio selection problem, as it extracts hidden patterns, avoiding fraud. The Jordan Elman networks have a superior performance that incorporates them in the model. Whilst the Hybrid Jordan Elman neuro-genetic on the inputs and outputs only of 1 layer is a fine model of excellent classification, performance and less processing time, in high risk of overfitting, as the Hybrid Jordan Elman with GAs in all layers and Cross Validation although in a marginal lower rank is the best option in all aspects plus it protects from overtraining. Hence the Jordan Elman models offer an excellent nonlinear regression result.

The core problem of portfolio optimisation as a part of the Logic in humans is answered by this AI imitation of natural neurons within our bodies. The principal philosophical question seeks an answer since the cradle of civilization, is our existence. This paper answers that Logic is dynamic in a linear part that adjusts, overriding new challenging ideas that offer higher potentials than the usual series of events. It may appear non-linear but it is consistent to the maximisation of utility, and investors’ financial welfare. Future work will analytically examine numerical results of utilities and the wealth impact of the models in the new trends of the bubbles.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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