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 out of the vast accounting data, financial statements, and other values, elaborating them on a new Jordan Elman hybrid network to provide safer financial evaluations.**

Keywords— integrated systems; generalized feedforward networks, jordan & elman neural networks; genetic algorithms; finance, non-linear regressions

I. INTRODUCTION

The weak explanatory power of the Gaussian probability distributions on returns and quadratic investor preferences does not support adequately the Markowitz's mean-variance criterion under the von Neumann-Morgenstern axioms of choice, (1992, 2009). The Power Utility demonstrated a marginal superiority on the Quadratic function, emphasizing on skewness, Loukeris et al. (2009). As investors prefer positive skewness, to earn high profits from extreme events, Boyle and Ding (2005), low kurtosis in lower risk probability because of the extreme outcomes in both sides of the distribution, Athayde and Flores (2003), Lai, Yu and Wang (2006). Thus more accurate detection of preferences require further higher moments, Loukeris et al. (2014a), 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 define theoretically the investment behavior, failing to approach the real behavior, Subrahmanyam (2007). Usual patterns such as overconfidence on private signals causes overreaction, such as the BE/ME effect, the long-run reversals, that cause momentum. The loss aversion, Barberis et al. (2001) is a robust cause for price fluctuations.

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 and Statman (1984a). Characteristics of gender such that the superiority of women's conservative tactic, the low frequency of trading, environmental, as 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 diferent 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. The Section 4 describes the data. Section 5 includes the results and Section 6 the conclusions.

II. 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, b), Loukeris et al. (2016), , Loukeris et al (2015b), Loukeris et al (2015a), Loukeris et al (2015) elaborated further higher moments on the utility function of the HARA family (Hyperbolic Absolute Risk Aversion). Based on the 5^{th} of hyperskewness and the 6^{th} of hyperkyrtosis moments Loukeris, Bekiros, and Eleftheriadis (2016) as:

$$Ut(R_{t+1})=aE_t(R_{t+1})-bVar_t(R_{t+1})+cSkew_t(R_{t+1})-dKurt_t(R_{t+1})+eHypSkew_t(R_{t+1})-fHypKurt_t(R_{t+1}) \quad (1)$$

Where

$$Kurt_t(R_{t+1}) = Var_t^2(R_{t+1}) \quad (2)$$

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

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

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

The general form of the utility function is:

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

where λ_v is the depth of accuracy on investors utility preferences to risk, $a_{\lambda v}$ 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:

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

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

III. METHODOLOGY

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

$$\min_x f(x)=\lambda Var(r_p)-(1-\lambda)E(r_p) \quad (8)$$

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

$$\min_x f(x)=\lambda\upsilon_\gamma[bVar_t(r_p)+dKurt_t(r_p)+fHypKurt_t(r_p)]-(1-\lambda)\upsilon_\gamma[aE_t(r_p)+cSkew_t(r_p)+eHypSkew_t(r_p)] + s^{\log\lambda_v} \quad (9)$$

$$\upsilon_\gamma=1-\varepsilon_\tau \quad (10)$$

$$r_P=\sum_i x_i r_i^* \quad (11)$$

where υ_γ the company's financial health, ε_τ the heuristic output (0 healthy, 1distressed), 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

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

let

$$Var_t^2(r_p) = z \quad (12)$$

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

as

$$z = y^2 = \sigma^4 \quad (14)$$

then

$$\min_x f(x) = \lambda\upsilon_\gamma Var_t(r_p)[b + dz + fz^2] - (1-\lambda)\upsilon_\gamma[a\mu + cE(x_i-\mu)y + eE(x_i-\mu)y^2] + s^{\log\lambda_v} \quad (15)$$

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 manipulation 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.

C. The Intelligent Portfolio Performance Optimisation 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 $U_{Pj}(f)$ recorded in $U^*_{Pj}(f) > U_{Pj}(f)$.

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

The flow chart of the IPSPS is in figure 1:

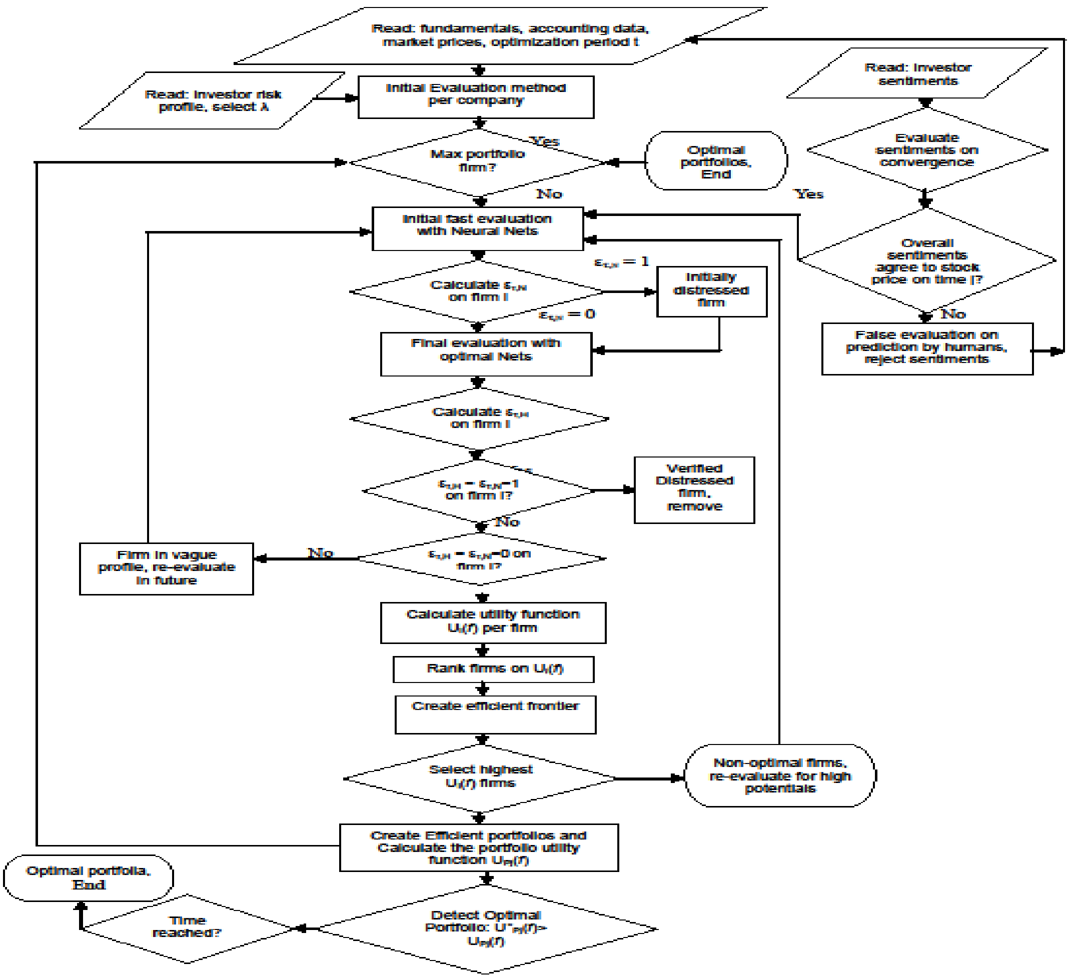

Figure 1. the IPPOS model

C.A. The initial processing phase

C.A.A Partially Recurrent Neural Networks

I. THE GENERALIZED FEEDFORWARD NEURAL NETWORKS

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

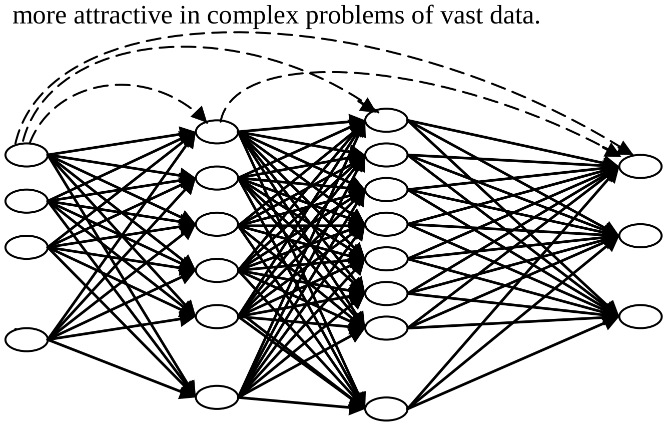

Fig. 1 The Generalised Feed Forward Network

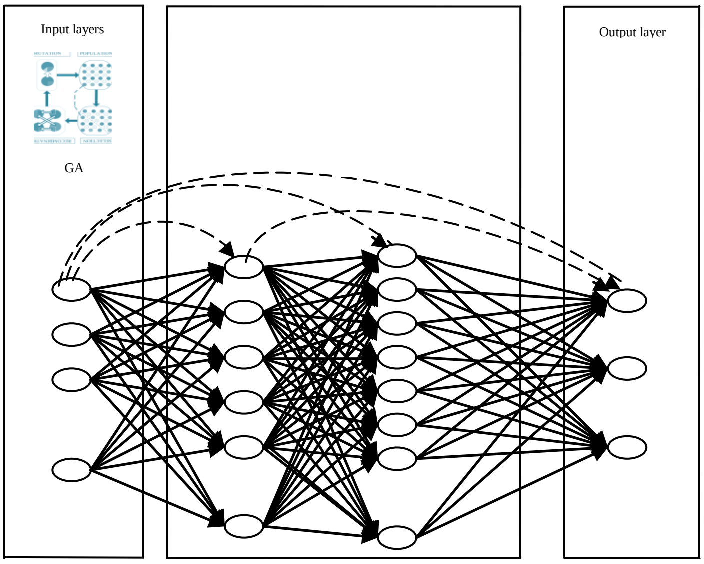

Fig. 2 The Hybrid Generalised Feed Forward Net of GA optimization into the inputs only

II. THE GENETIC ALGORITHMS IN THE GENERALIZED FEEDFORWARD HYBRIDS

The importance of each one of the 16 financial inputs in the Generalised 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

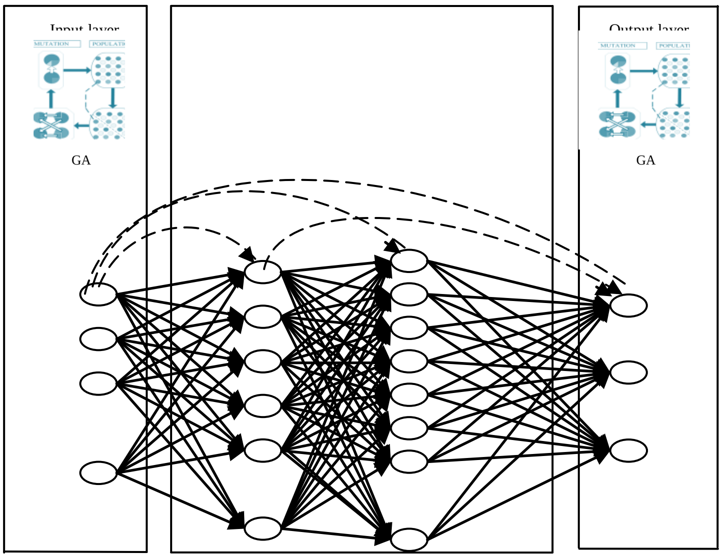

Fig. 3 The Hybrid Generalised Feed Forward Net of GA optimization into the inputs and outputs only

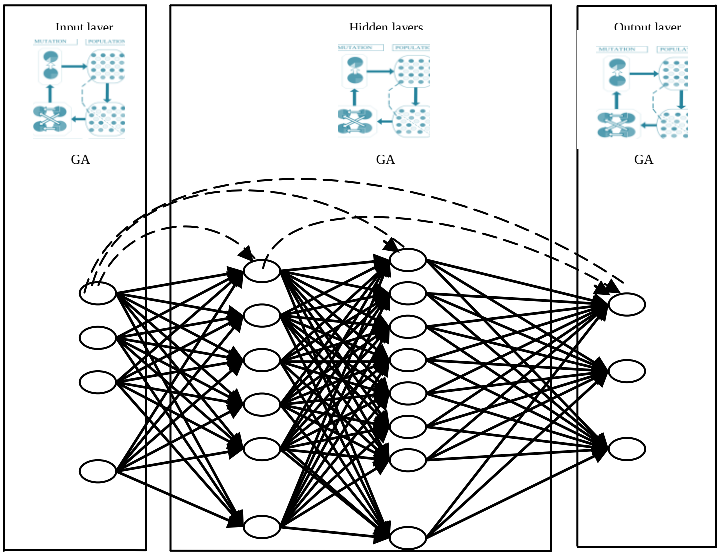

Figure 4. The Hybrid Generalised Feed Forward Net of GA optimization and Cross Validation in all the layers

inputs and outputs layers only, iii) into all the layers, iv) into all the layers with cross validation.

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.

III. THE JORDAN ELMAN NEURAL NETWORKS

A. *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 **[6]**. The Partial Recurrent Networks are i) the Jordan network, ii) the Elman network and iii) the Multi –Step Recurrent network.

B. *The Jordan Network*

The Jordan neural nets **[7]**, **[8]**, include the context neurons that receive a copy from the output neurons and

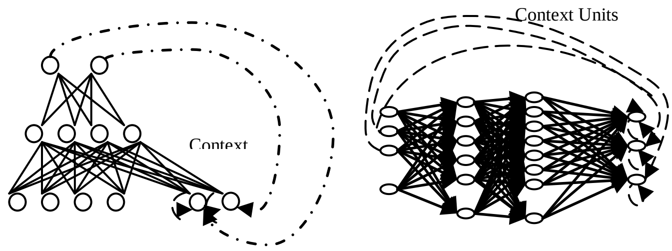

Fig. 1 The single layer Jordan Net-[Left], The Multilayer Jordan Net, λ ϵ [0, 1]-[Right]

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

C. *The Elman Network*

The Elman nets **[9]**, 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.

D. *The Multi-Step Recurrent network*

The Multi-Step recurrent network, **[10]**, has feedback connections directed from the output neuron to input layer. The context neurons memorise previous outputs of the network.

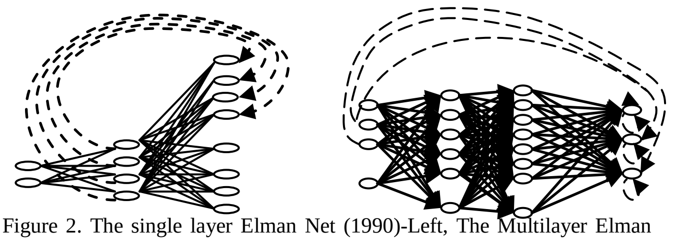

Figure 2. The single layer Elman Net (1990)-Left, The Multilayer Elman Net (1990)-Right

E. *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.

IV. *THE GENETIC ALGORITHMS IN THE JORDAN-ELMAN HYBRIDS*

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.

A. *Training Jordan & Elmans and the linear systems theory*

The training process for Jordan and Elman networks is:

1. Activations of the context neurons are initialized at 0 on the first instant.
2. External input (x(t)...,x(t-d)) at instant t and neurons context activations are sequenced to determine the input vector u(t) to the network, which is propagated towards the output, giving a prediction at instant t+1.
3. The back propagation algorithm is applied to modify networks weights
4. Time variable is increased by 1 and the procedure returns to step 2

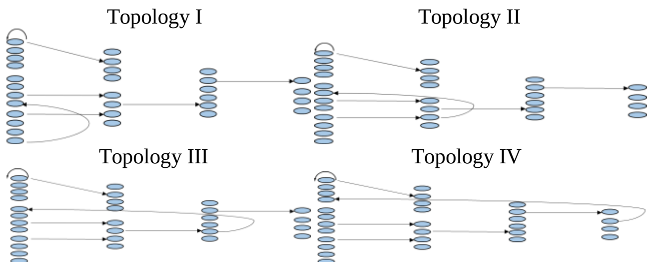

Figure 3. Processing in Jordan and Elman nets under the 4 different topologies

C.A.F The Genetic Algorithms in the Jordan-Elman Hybrids

The significance on each one of the 16 financial inputs in all the Jordan Elman networks 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 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. The Batch learning was preferred to update the weights of hybrid neuro-genetic JE, after the presentation of the entire training set. The Genetic Algorithms 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. JE nets require multiple training to achieve the lowest error.

V. 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. 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.

V. 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

TABLE I. Overall ranking of the optimal Generalized FeedForwards

Table 4. Optimal GFF Overall ranking		**Active Confusion Matri**					**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***	***0,1705***	***0,908***	***5.776***	***-1907,09***	***-1796,44***	3h 19’ 25’’
GFF GA all	*3*	*97,14*	*2,845*	*17,885*	*82,10*	*0,128*	*0,304*	*0,834*	*8,3435*	*40259,12*	*284,345*	4h 20’ 25’’
	1	*97,56*	*2,425*	*18,805*	*81,18*	*0,133*	*0,3155*	*0,8275*	*8,2435*	*-723,475*	*-271,82*	3h 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*	25h 46’ 34’’
CV		*98,32*	*1,67*	*29,355*	*70,63*	*0,149*	*0,3535*	*0,8125*	*7,073*	*1608,295*	*3495,495*	
GFF NN	*1*	*97,73*	*2,26*	*21,095*	*78,89*	*0,138*	*0,328*	*0,8215*	*9,6755*	*-1225,82*	*-1111,95*	14’’
GFF NN, CV	*8*	*98,23*	*1,755*	*26,14*	*73,85*	*0,143*	*0,338*	*0,814*	*9,2845*	*709,44*	*2041,355*	1’ 03’’
CV		*98,23*	*1,755*	*26,14*	*73,85*	*0,143*	*0,338*	*0,814*	*9,2845*	*709,44*	*2041,355*	
GFF GA inputs	*10*	*97,98*	*2,005*	*26,6*	*73,16*	*0,144*	*0,341*	*0,8125*	*9,4695*	*1219,39*	*2873,695*	7h 44’ 32’’
GFF GA all	*8*	*98,57*	*1,42*	*26,6*	*73,39*	*0,140*	*0,3295*	*0,8215*	*8,329*	*1262,655*	*2959,695*	29h 50’ 17’’
GFF GA all,	*1*	*97,98*	*2,005*	*24,305*	*75,68*	*0,145*	*0,343*	*0,8105*	*8,646*	*-1219,07*	*-1126,3*	2h 27’ 41’’

TABLE II. Overall ranking of the optimal Jordan Elman models

Table 4. Optimal JE Overall ranking		**Active Confusion Matri**					**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*	*2h 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*	*1h 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 III. Overall ranking of the optimal Generalized FeedForward

Model	Active Confusion Matrix					Performance						Time
	Layers	**0→0**	**0→1**	**1→0**	**1→1**	**MSE**	**NMSE**	**r**	**%error**	**AIC**	**MDL**	
Jordan Elman input-outp GA	*1*	*99.83*	*0.16*	*3.20*	*96.78*	*0.022*	*0.052*	*0.983*	*3836*	*-2481.7*	*-2355.07*	*55' 18''*
Jordan Elman input-outp 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''
Jordan 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*	*2h 35'29''*
CV		99.83	0.16	0.91	99.08	0.023	0.056	0.971	28.511	-2425.7	-2273.5	
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*	*1h 38'53''*
Jordan 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 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''
Jordan 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''
MLP NN, 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*	*0,1705*	*0,908*	*5.776*	*-1907,09*	*-1796,44*	3h 19' 25''

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.

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.

VI. Conclusions

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.

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