Computational Intelligence in Portfolio Optimization – the IPSOS Model

Loukeris N., Eleftheriadis I.,
University of Macedonia
dept. of Business Administration
Egnatias 156, 540 06 Thessaloniki, Greece
nloukeris@uom.edu.gr

Abstract— **Although returns distributions are complex, they can't avoid manipulation in any form. We propose a new methodology, the Intelligent Portfolio Selection & Optimisation System – IPSOS that takes into account hidden information within the extended accounting data and financial statements, among other values incorporates them on a new Jordan Elman hybrid network to provide safer financial evaluations.**

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

I. Introduction

The Markowitz's mean-variance criterion follows the von Neumann-Morgenstern axioms of choice only under Gaussian probability distributions on returns and quadratic investor preferences. Markets have clearly shown that both conditions do not hold, Merton (1992, 2009), as investors have different patterns than the quadratic utility function, neither returns are n.i.i.d. The marginal superiority of the Power to the Quadratic utility function, emphasizing on skewness, was underlined by Loukeris et al. (2009). In reality the investors prefer positive skewness, earning high profits from extreme events, Boyle and Ding (2005), low kurtosis or lower risk probability because of the extreme losses or profits in both sides of the distribution, Athayde and Flores (2003), Lai, Yu and Wang (2006). As Loukeris et al. (2014a) showed, higher precision in investor's preferences demand a more advanced analytical approach, in the form of further higher moments. Those moments, such as the HyperSkewness, $m_{5,}$ in the *E(U)*, reduce the information uncertainty on the investor, and thus the mispricing from various reasons either endogenous eg. BE/ME and momentum within crossectional regressions, or exogenous such as the manipulation, the corruption, or fraud. But in reality theories of rational utility maximizers aren't an optimal alternative to behavioral approaches as they examine theoretical aspects of how investors should behave, and not how investors do behave; in a distance from the real markets, Subrahmanyam (2007). Evidence conclude that non-risk related characteristics, such as stock returns predictors, are far more compelling than the risk-based ones. Also overconfidence on private signals causes overreaction, like the BE/ME effect, the long-run reversals, that cause momentum.
Barberis et al. (2001) and Barberis and Huang (2001) used loss aversion -the greater disutility suffer of investors from a wealth loss than an equivalent gain- into utility functions, showing that in individual stocks it leads to excess price fluctuations. Grinblatt and Han (2005) argue that loss aversion can help explain momentum.
On the investor moods Shefrin and Statman (1984a), Odean (1998), indicate a disposition effect among investors, to sell winners too soon and hold on to losers too long, although past winners do better than losers. Coval and Moskowitz (1999) show local optima limitations to mutual fund managers as they prefer local showing a proclivity for stocks headquartered in their region. Hong et al. (2005) suggest the strong factor impacting portfolio decisions of the word-of-mouth effect by social interaction between money managers. Barberis and Shleifer (2003), argue that the tendency of investors to heuristically categorize objects can lead to the emergence of style-based mutual funds.
Further differences cause significant investment performance alternations: the superiority of women's conservative tactic, the low frequency of trading, the good weather, the day of the week, the close proximity of the company to the investor are key features for lucrative investments. The feasible portfolios set, largely inefficient, is rejected by at least risk-averse investors. The efficient frontier of the remaining portfolios is selected regarding the investor behavior, in a trade-off between the profitability parameters defined in the prime order moments (mean, skewness, hyperskewness) of desirable higher values, towards the risk parameters, the even order moments (variance, kurtosis, hyperkurtosis) required to be low. The optimal selection problem follows a two phase process.
The objective of this research is to investigate the first phase of the optimization problem, and to propose an integrated system that will perform the selection and continuous optimization process using advanced methods of Artificial Intelligence and Finance. The single period model is examined, as we introduce six different Jordan Elman hybrid net models of 11 different topologies each, to produce the efficient frontier surface. The scope is quintuple:

A. to investigate in depth the investors behavior in higher moments
B. to introduce an improvement of the isoelastic utility
C. to further develop the Markowitz's portfolio theory, in fundamentals evaluation, prices, and other available info,

D. to examine the efficiency of the Jordan Elman networks in neuro-genetic hybrids or neural net forms on various topologies to a new learning process,
E. to introduce the integrated model IPSOS as a modern solution to portfolio selection and optimization problems.

The Jordan Elman neural networks, are examined on 2 different neural forms and 11 topologies and 4 hybrid forms where genetic algorithms optimise their parameters. These four different variations, a new learning process, the Batch, updates the trained weights of the model ex-ante, including new aspects on the training process in higher rates of convergence. The portfolio optimisation problem is non-deterministic and hence the most effective way of resolving it is through heuristics. We examine all the 2 neural and 4 hybrid Jordan Elman networks in 66 models to define the most optimal classifier that will be used in the integrated system IPSOS.

The complex human investment procedure can't be accurately described into the markets, although we approach it through advanced isoelastic utility functions and artificial intelligence.

This research in Section 1 provides description on the EMH, the higher moments and the Isoelastic utility we use. Sections 2 is about investing behavior, Section 3 offers the portfolio selection model in the Isoelastic utility function, the new portfolio selection constraints with fundamentals and Artificial Intelligence models. The Section 5 supports the data analysis. Section 6 includes the results and Section 7 the conclusions.

II. BEHAVIOR AND MODELLING

Diversification exists rarely in real portfolios investors own only a few stocks. The expected returns do not vary in the cross-section only because of risk differentials across stocks. Existing empirical work is obsessed with data-mining. Empirical research confirmed the evidence out-of-sample, both in terms of time-periods as well as cross-sectional across different countries. The connection of loss to risk aversion thus our model is supported, whilst the non-rational effects of time, gender, firm's proximity to investor, time, etc, enhance the various non-linear effects that the investment decision is exposed to. We approach the loss-aversion and the non-linear constraints with the integrated Intelligent Portfolio Selection and Optimization System (IPSOS).

III. FURTHER HIGHER MOMENTS

Allocations of returns are not n.i.i.d., and EMH does not hold. Investors are more sensitive to their potential losses, Subrahmanyam (2007), thus we will try to model the overall preferences, even those that incorporate the non-rational trends in terms of non-linearity, or non-causality that guide them. Investors distribute their utility balancing perceptions and fears, towards earnings. They expect a logical level of return, although the fear of loss subconsciously magnified, produces significant decisions. In general investors demonstrate a risk averse or risk neutral profile, thus fear can easily to manipulate behaviors. In euphoria periods the dominant role of the fear to lose excess profits, as in recessions the fear of maximising losses, usually magnify non rational herding reactions on markets.

We introduce an integrated model that examines in all the parameters that consist a significant influence on investors. Loukeris et al. (2014a, b) noticed that on the implied utility function of the HARA family (Hyperbolic Absolute Risk Aversion) the 5th of hyperskewness and the 6th of hyperkyrtosis moments should be used in the form of

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

Where

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

$$HypKurt_t(R_{t+1}) = Kurt_t^2(R_{t+1}) = Var_t^4(R_{t+1}) \quad (3)$$

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

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

noticing that the Makowitz approach can have a broader alternative relaxing its essential assumption on the normaly distributed prices. Thus the HARA utility function (1) is a series of higher order moments, extended to the desired level of analysis. A 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 towards risk, depending on the behavior, $a_{\lambda v}$ 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.

IV. METHODOLOGY

A. Past approaches

The convex problem of quadratic utility maximization, Markowitz (1952), is insufficient in real markets. Maringer and Parpas (2009) considered applicable higher order moments:

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

B. Problem Definition

Loukeris et al. (2014a, b) noticed the significance of further higher moments in the model, to describe preferences. The problem, is:

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

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

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

where υ_γ the financial health of the company (binary: 0 towards bankruptcy, 1 healthy), ε_τ the heuristic model output that is the evaluation result (binary: 0 healthy, or 1distressed), s the social effect of non-rational features, as noise eg. gender, local proximity, day of week, weather, frequency of trading, preference of on-line trading etc., r_i^* the return of stock i that belongs to the efficient frontier and is superior than the others, x_i their weights. The superiority relation of the selected stocks within the portfolio is i^* *sup* j if and only if $R_t(i^*)>R_t(j)$, analysed into:

$$E_t R_t(i^*) > E_t R_t(j) \quad (12)$$

$$Skew_t R_t(i^*) > Skew_t R_t(j) \quad (13)$$

$$HypSkew_t R_t(i^*) > HypSkew_t R_t(j) \quad (14)$$

The stocks do not fulfill all the superiority conditions are non-optimal and are exempted from the efficient frontier. Thus given Loukeris et al. (2014a, b):

$$U_t(R_t(_i)) = \sum^{\omega}_{\lambda v=1}(-1)^{\lambda v+1} a_{\lambda v}/n\sum^{n}_{i=1}(x_i - \sum x_i/n)^n \quad (15)$$

then

$$U_t(R_t(_i^*)) > U_t(R_t(x_j)) \quad (16)$$

Hence

$$U_t(r_p) = \sum U_t(R_t(_i^*)) \quad (17)$$

The previous is identical to

$$\max_x E(U_P(w, \lambda)) \quad (18)$$

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

let

$$Var_t^2(r_p) = z \quad (20)$$

$$Var_t(R_{t+1}) = y \quad (21)$$

as

$$z = y^2 = \sigma^4 \quad (22)$$

then

$$min_x f(x) = \lambda\upsilon_\gamma Var_t(r_p)[b + dz + fz^2] - (1-\lambda)\upsilon_\gamma[a\mu + cE(x_i-\mu)y + eE(x_i-\mu)y^2] + s \quad (23)$$

The non-convex problem, requires strong heuristics to be resolved. For $eE(x_i-\mu) \neq 0$, $\Delta = [cE(x_i-\mu)]^2 - 4eE(x_i-\mu)a$. The real roots are $y_{1,2} = [-cE(x_i-\mu) \pm \sqrt{\Delta}]/2eE(x_i-\mu)$ thus the problem (23) transforms to

$$min_x f(x)=\lambda\upsilon_\gamma Var_t(r_p)[(z-[-d-\sqrt{d^2 - 4fb}/2fb])(z+[-d+\sqrt{d^2 - 4fb}]/2fb])]-(1-\lambda)\upsilon_\gamma[(y-[[-cE(x_i-\mu)-\sqrt{[cE(x_i-\mu)]^2 - 4eE(x_i-\mu)a}/2eE(x_i-\mu)]])(y+[-cE(x_i-\mu)+\sqrt{[cE(x_i-\mu)]^2 - 4eE(x_i-\mu)a}/2eE(x_i-\mu)]])] + s \quad (24)$$

The new contribution is that we extract hidden accounting and financial patterns that can make the difference on the stock's evaluation. The semi-strong form of information that typically is legal for a common investor, according to the EMH, is quite vague, because of the vast amount of noise and the numerous manipulation attempts from other agents. The fraud and manipulation infections are a significant risk to investors quite frequently. Internal information is a usual reason for stock manipulation. Thus under (10) and (24) we filter the distressed companies with no significant potentials from portfolios. The evaluation υ_γ, in (10) is more important than the investor's risk behavior, as they have a reverse influence in υ_γ/λ. The $min_x f(x)$ equality in (23) declares a categorical, objective influence of an asset is more influential than subjective investors' behavior. The flow chart of processes is described in figure 1.

C. The Intelligent Portfolio Selection & Optimisation System – IPSOS

The integrated model IPSOS - Intelligent Portfolio Selection & Optimisation System on the first step reads the fundamentals, the accounting data, the market prices, and the preferred optimisation period t.

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:

C.A. The initial processing phase

C.A.A Partially Recurrent Neural Networks

The Partially Recurrent Networks are MLP nets where a few recurrent connections are introduced. The input layer of Partially Recurrent Networks includes two types of neurons: the neurons that behave as inputs, receiving external signals, and the context neurons or neurons of state, that remember past actions and take output values from one of the layers delayed by one step. Internal states, that function as a short-term memory, of the partially recurrent neural nets, can predict time series, as they can represent information about the preceding inputs Stagge and Senho (1997). The Partial Recurrent Networks are i) the Jordan network, ii) the Elman network and iii) the Multi –Step Recurrent network.

C.A.B The Jordan Network

Jordan (1986a, 1986) created the Jordan neural nets, where the context neurons receive a copy from the output neurons and from themselves, thus many context neurons are the outputs. The recurrent connections from the output layer to the context neurons have an associated parameter of constant value: m ϵ (0, 1).

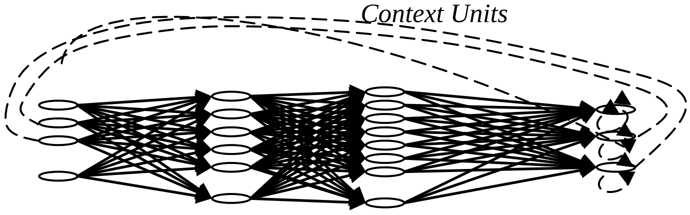

Fig 2. The Jordan Network (1986), λ ϵ [0, 1]

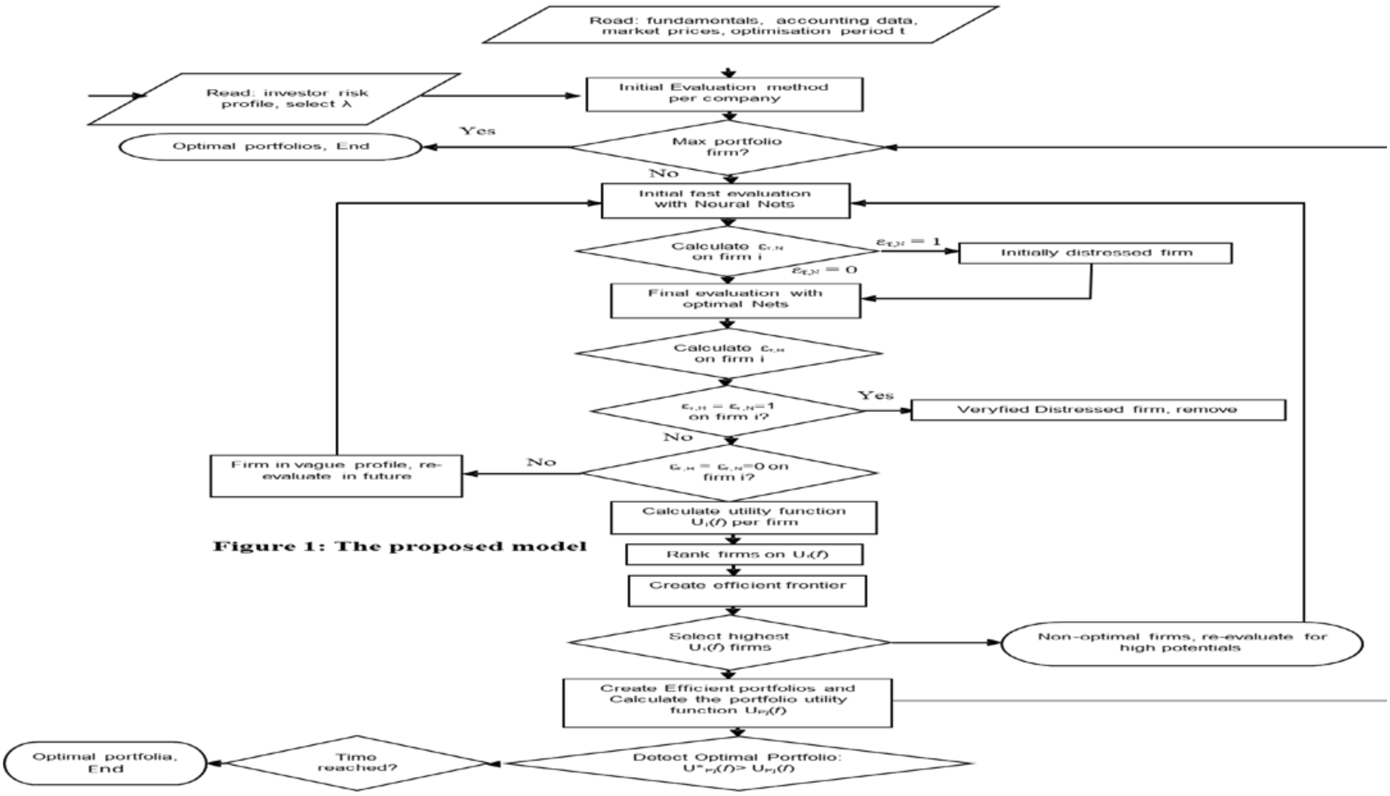

Figure 1: The proposed model

C.A.C The Elman Network

Elman (1990) created the Elman nets, where the context neurons receive a copy of the networks' hidden neurons and these connections do not need to associate any parameter. Thus the number of the context neurons is identical to the number of hidden neurons into the network. The remaining activations are calculated similarly as in a MLP, considering the sequence of external inputs and context neurons as the vector input to the network.

C.A.D The Multi-Step Recurrent network

In the Multi-Step recurrent network, Galvan and Isasi (2001), the feedback connections are directed from the output neuron to input layer. The context neurons memorise previous outputs of the network. The number of input and context neurons is replaced in every sampling time.

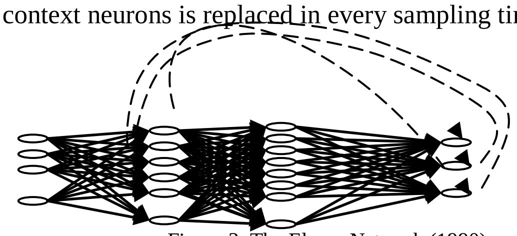

Figure 3. The Elman Network (1990)

C.A.E The Jordan Elman Networks

The configuration of all the Jordan Elman nets in the current research is selected to feed the context units with the input samples, providing an integrated past of the input. The context unit remembers the past of its inputs using a recency gradient, forgetting the past with an exponential decay, and controls the forgetting factor through the Time constant that here is selected to be the IntegratorAxon function of 0.8 s time –of a longer memory depth and a slower forgetting factor. There were standard 4 neurons per hidden layer using as the transfer function the TanhAxon, the learning rule was the Momentum function, on a value of 0.7 as a momentum and changing step size per hidden layer in a scale of 0.1.

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:

a) the Step Size and
b) the Momentum Rate.

JE nets require multiple training to achieve the lowest error.

C.A.G Data

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

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 was chosen to detect the

TABLE II. Overall ranking of the optimal Jordan Elman models

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*	*0.973*	*3.836*	*-2481.7*	*-2355.07*	*55' 18''*
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, CV	*2*	*99.66*	*0.33*	*5.50*	*94.49*	*0.023*	*0.055*	*0.972*	*12.326*	*-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*	*41.275*	*-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''

performance of JE Networks:

i) JE Neural Nets,
ii) JE Neural Nets with Cross Validation,
iii) JE Nets with GA in input layer only,
iv) JE Nets with GA in input and output layers only,
v) JE Nets with GA in all layers,
vi) JE Nets with GA in all layers and Cross Validation.

V. Results

The most optimal performance on the in sample Jordan Elman models was observed on the JE Hybrid of GA optimization on the input 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 minutes 18 seconds

The second place was taken by the JE NN of 1 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 0.022 for the MSE, 0.053 for the NMSE, 37.6% from the overall error, in a very high fitness of the data on the model as r was 0.972, and a great impartiality of AIC in -2407.85, in the fastest time of only 4 seconds, but exposed to over-training phenomena.

An almost identical performance 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 hours 35 minutes 29 seconds

VI. Conclusions

The integrated model IPSOS - Intelligent Portfolio Selection & Optimisation System, offers a more detailed approach into the real time portfolio selection problem. The main advantage of this system is that by extracting hidden patterns it tries to avoid manipulation, and speculation games. The Jordan Elman networks have a promising performance of high calibration that can allow them to be a part of this model or its future developments. More over the Jordan Elman neuro-genetic Hybrid on the inputs and outputs only of 1 layer is a very reliable model of excellent classification abilities, performance and a low computing time, but in a higher risk of overfitting, whilst 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. Thus the Jordan Elman networks provide an excellent nonlinear regression to Corporate Financial Evaluation.

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