Selecting Optimal Portfolio in Generalised Feed Forward Networks And Self Organized Features Maps Hybrids

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***Abstract*—We evaluate the performance of 70 Generalised Feed Forward and 60 Self Organized Feature Maps models of plain and hybrid form to define the optimal classifier in portfolio selection. We also apply it on a novel model of optimal portfolio selection in hedging aspects.**

***Index Terms* — Genetic Algorithms, Generalised Feed Forward, Hybrid Networks, Self Organized Feature Maps, Hedge Management, Portfolio Optimization**

I. Introduction

The 2 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 article evaluates the first step that resolves the second step. We thoroughly examine the systems of neural or neuro-genetic

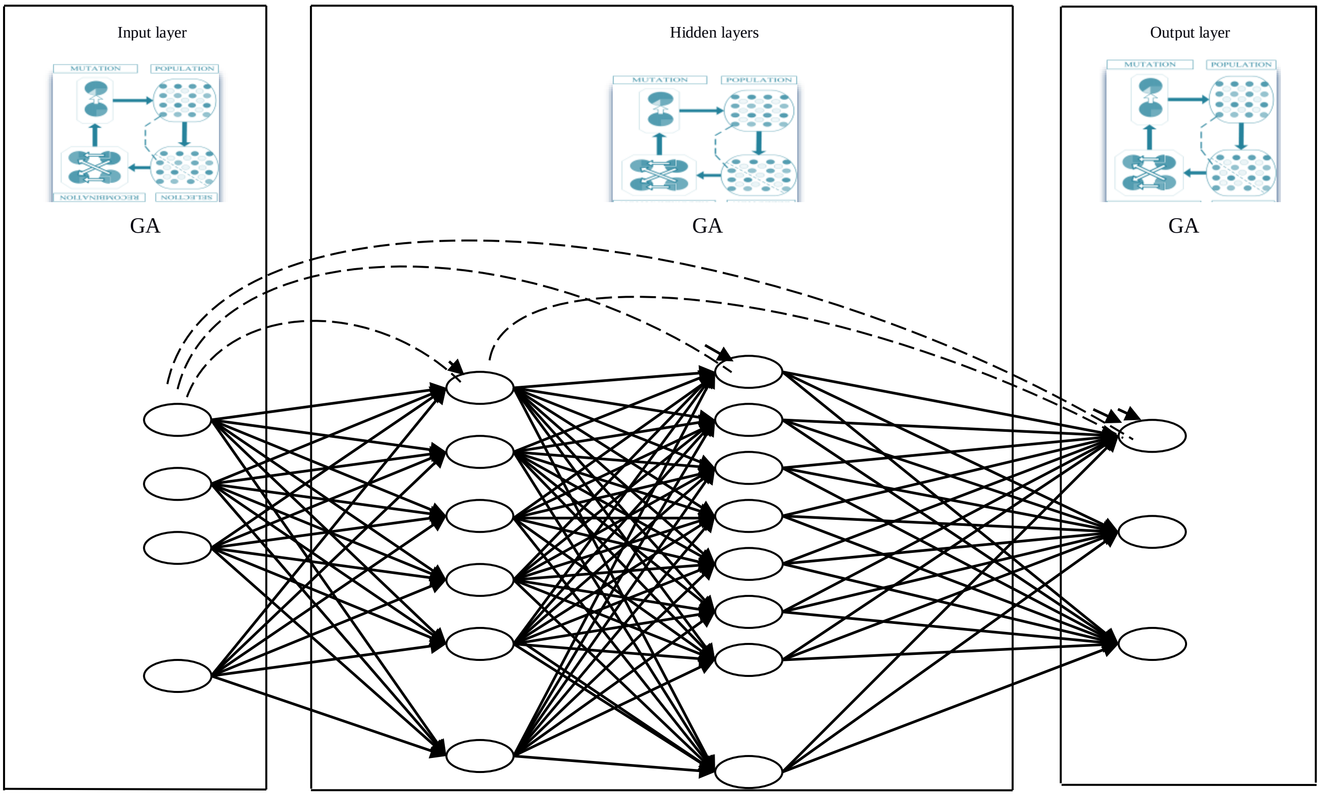

Figure 1. The Hybrid Generalised Feed Forward networks, of GA optimization in all layers and CV.

hybrids: 70 Generalised Feed Forward and 60 different Self Organized Feature Maps networks in 20 neural networks and 50 GFF hybrids as 20 neural nets and 40 hybrid neuro-genetic SOFM models of alternative topologies that seek the most efficient neural model to classify the portfolio selection.

II. The Hybrid Generalised Feed Forward networks

The Generalised Feed Forward networks, (*figure 1*) are a generic form of the Multi Layer Perceptrons that are able to let their synapses jump over one or more layers. Into the GFFs we apply an initial MLP as in each layer its signals feeds forward all the forthcoming layers. The actual performance of the GFFs revealed that they are much more efficient resolving classifiers to the problem than the MLPs, in much shorter time, for a similar number of neurons.

III. Self Organized Features Maps

The Self Organized Features Maps-SOFM neural network, Kohonen (1982), or Kohonen map, is optimized for clustering, and data examination. The SOFM is trained in unsupervised learning forming a two-dimensional map. This discretised input surface of the training set reduces dimensionality. The SOFMs use competitive learning, alternating from the other neural nets. The 16 financial indices have an unknown significance in the SOFM nets and we incorporate Genetic Algorithms-GA, Holland (1975/1992), to determine it. Each model is trained multiply to conclude in the inputs of the lowest error. The GAs are elaborated in different hybrids both for the MLPs and SOFMs of the: i) inputs layer only, ii) inputs and outputs layers only, iii) all layers and cluster centers, iv) all layers and cluster centers with cross validation, in different topologies. The Batch learning adjusts the weights of hybrid SOFM.

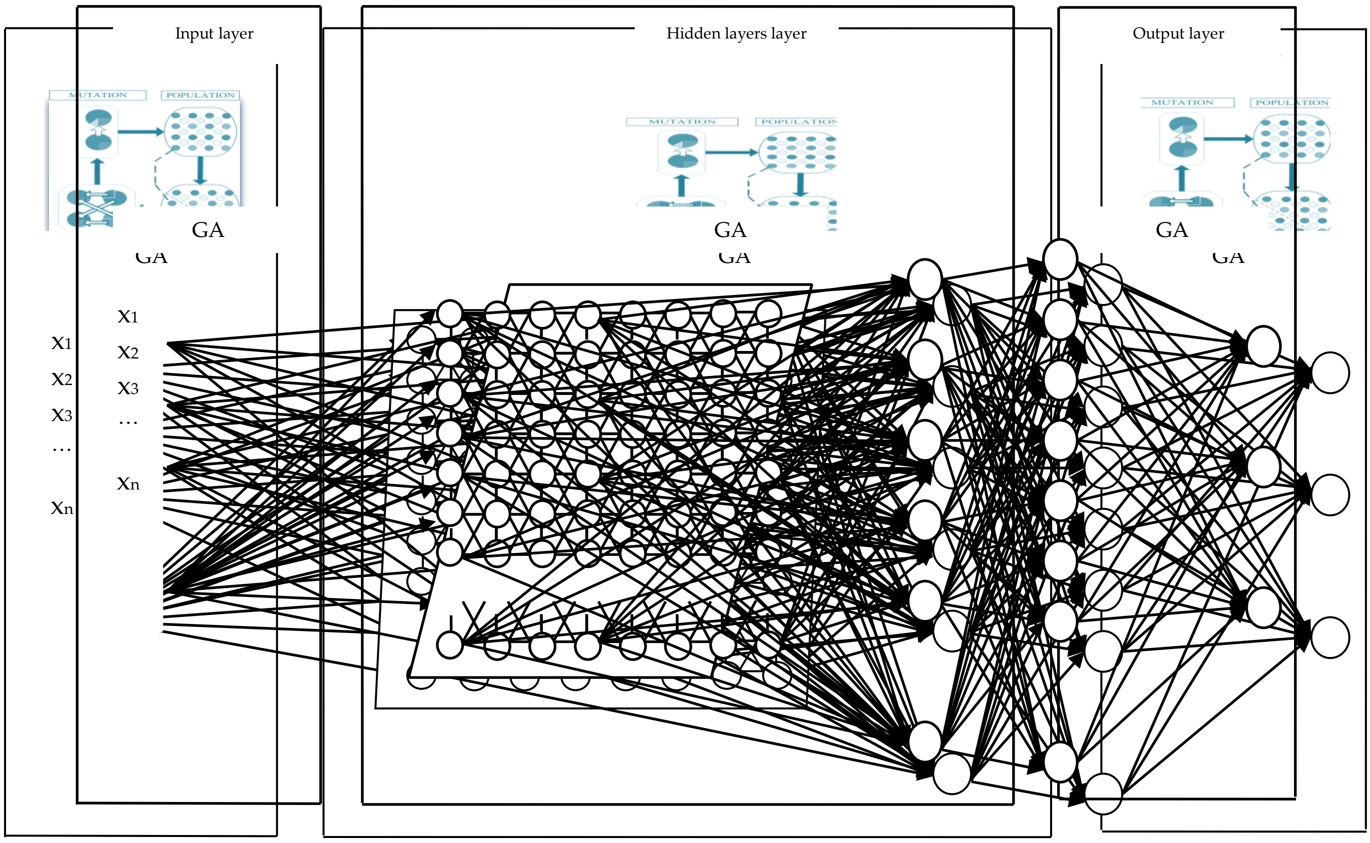

Figure 2. Hybrid Self Organized Feature Maps with Genetic optimization on all layers and Cross Validation, Loukeris, Chalamandaris, Eleftheriadis (2019),

IV. Data of neural computation

The data came 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, by bank experts Courtis (1978). The test set was 50% of overall data, and the training 50%. The 1411 companies are unique, the observation has discrete frequency in 3 different annual values and the average is implemented, Courtis (1978), the dependent value ε_τ is binary, in 0 for the healthy, and 1 for the distressed companies. The classification process Kohonen (1982) of the SOFM models is processed by the appropriate classifier, Principe, deVries, Kuo and Oliveira (1992), Principe, Euliano, and Lefebvre, (1999).

IV. Results of the Generalised Feed Forward models

The GFF hybrid of 1 layer in Genetic Algorithms optimisation on the inputs and outputs layers only was the optimal performance classifier in high correct classifications of the healthy and the distressed companies at 98.9% and 88.52% respectfully, very high fitness of the model to the data as r was 0.908, the lowest error as MSE was 0.072, NMSE 0.170 and percentage error 5.77, whilst the AIC was very low at -1907.09 indicating impartiality and a time of 3h 19m 25s.

The next rank was taken by the hybrid GFF of 3 layers in GA optimization in all layers, in an almost fine classification, a high fitness of the model to the data at r 0.834, low error, and impartiality in 4h 20m 25s.

A slightly inferior performance had the hybrid GFF of 1 layer and GA optimization in all layers, in terms of classification, fitness, and error, whilst the impartiality was higher, in a time of 3h 19m 25s Loukeris and Eleftheriadis (2016).

Table 1. Ranking of the optimal GFF models overall, Loukeris and Eleftheriadis (2016)

Models		Active Confusion Matrix				Performance						
	Layers	0→0	0→1	1→0	1→1	MSE	NMSE	r	%error	AIC	MDL	Time
GFF input-output GA	1	98.90	1.085	11.465	88.52	0.072	0.170	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	8.343	-786.38	284.34	4h 20' 25"
GFF GA all	1	97.56	2.425	18.805	81.18	0.133	0.315	0.827	8.243	-723.47	-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	0.353	0.812	7.023	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	42.5’’
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	7h 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	29h 50' 17"
GFF GA all, CV	1	97.98	2.005	24.305	75.68	0.145	0.343	0.810	8.646	-1219.07	-1126.3	2h 27' 41"
CV		98.4	1.59	24.765	75.22	0.139	0.330	0.821	8.686	-1242.55	-1149.79	
GFF NN	10	98.65	1.34	31.185	68.80	0.147	0.348	0.811	8.454	1557.50	3419.165	57’’

V. Results of the SOFM models

The optimal overall classifier was the Hybrid SOFM of 2 layers GA optimization in all layers and Cross Validation, in 98.82% and 59.63% correct classification of the healthy and distressed companies that produces an acceptable classification, a medium fitness to the model r at 0.656, an average level of error, significant partiality in 740.06 AIC, requiring a significant 2 hours 35 minutes and 29 seconds of processing time.

Second was ranked the SOFM hybrid with GAs that optimized all layers, medium classification in 99.07% and 36.23% of the healthy and distressed firms, a medium fitness to the model at 0.614, medium error, higher partiality at 1290.15 AIC, and higher time of 2 hoursa 26 minutes 13 seconds.

Third was the SOFM hybrid with genetic optimization in the inputs and output layers only of 2 layers, in 97.57% and 43.16% correct classifications of the healthy and distressed companies, a medium fitness of the model to the data at 0.581, slightly lower error, an Akaike at 389.25 indicating a significant partiality, with a lower time of 1 hour and 15’ 43’’.

Table 2. Ranking of the optimal SOFM models overall

Models		Active Confusion Matrix				Performance						
	Layers	0→0	0→1	1→0	1→1	MSE	NMSE	r	%error	AIC	MDL	Time
SOFM GA all, CV	2	98.82	1.17	59.63	40.36	0.434	1.028	0.656	14.67	740.06	1589.85	2h 35' 29"
CV		97.57	2.425	57.33	43.16	0.430	1.017	0.726	15.21	734.16	1683.48	
SOFM GA all	2	99.07	0.92	63.76	36.23	0.487	1.151	0.614	7.30	1290.15	2440.69	2h 26' 13"
SOFM in-out GA	2	98.45	1.59	71.55	28.43	0.416	0.984	0.581	19.35	389.25	1034.28	1h 15' 43"
SOFM in-out GA	0	98.99	1.01	72.01	27.98	0.556	1.316	0.550	12.99	188.54	573.76	1h 41' 57"

VI. Concluding Remarks

The GFF hybrids had a significantly superior performance than the SOFMs.

Specifically the overall optimal classifier between the examined groups of GFFs, and SOFMs was the GFF Hybrid of GA optimization on the input and output layers only, with 1 hidden layers, very good classification, and fitness, low error, impartiality and low computing time.

The second overall best classifier was the GFF Hybrid of GA optimization in all layers, with 3 hidden layers, very good classification, and fitness, low error, impartiality and higher time.

Third overall classifier was the GFF of GAs in all layers and Cross Validation, in 1 hidden layer, very good classification and fitness as well, lower error, impartiality and medium time.

The SOFMs underperformed in all cases and were ranked between the positions from 11^{th} to 13^{th} in grounds of optimal performance.

Unfortunately the best SOFM model had the 11 rank of lower classification, medium fitness and higher error, in a shorter computational time. Hence we notice that the simple MLP core with feedforward signal performs betters than the Kohonen architecture in this data classification case. The simple design where the synapses jump over one or more layers of GFs is more efficient than the two dimensional maps and the competitive learning process of the Kohonen core in the SOFMs. Even the evolutional computing alternative of Genetic Algorithms couldn’t provide a robust competitive advantage to the Kohonen approach. In our case a simple hybrid of feedforward process with minimal evolutional support was the most effective solution in the specific problem.

Table 3. Overall ranking of the optimal GFF and SOFM models

Models		**Active Confusion Matrix**				**Performance**						
	Layers	**0→0**	**0→1**	**1→0**	**1→1**	**MSE**	**NMSE**	**r**	**%error**	**AIC**	**MDL**	**Time**
GFF input-output GA	1	98.90	1.085	11.465	88.52	0.072	0.170	0.908	5.776	-1907.09	-1796.44	3h 19' 25"
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