Scalability of a methodology for generating technical trading rules with GAPs based on Risk-Return adjustment and incremental training

de la Cal, E.A.[1], Fernández, E.M.[1], Quiroga, R.[2], Villar J.R.[1], and Sedano, J.[3]

[1] Computer Science Department, University of Oviedo, Campus de Viesques, 33203 Gijn, Spain
[2] Cuantitative Economy Department, University of Oviedo, Campus del Cristo, 33006 Oviedo, Spain
[3] Instituto Tecnologco de Castilla-Len, Lopez Bravo 70, Pol. Ind. Villalonquejar, 09001 Burgos, Spain

Abstract. In previous works a methodology was defined, based on the design of a genetic algorithm *GAP* and an incremental training technique adapted to the learning of series of stock market values. The *GAP* technique consists in a fusion of *GP* and *GA*. The *GAP* algorithm implements the automatic search for crisp trading rules taking as objectives of the training both the optimization of the return obtained and the minimization of the assumed risk. Applying the proposed methodology, rules have been obtained for a period of eight years of the *S&P500* index. The achieved adjustment of the relation return-risk has generated rules with returns very superior in the testing period to those obtained applying habitual methodologies and even clearly superior to *Buy&Hold*. This work probes that the proposed methodology is valid for different assets in a different market than previous work.

1 Introduction

Most publications on trading rules generation by soft computing techniques, *GP* systems [1], [2], [3] establish as a unique objective of the genetic algorithm, the maximization of the excess of return over *Buy&Hold*[4]. That is, maximize the return of the rules in the training period without taking into account the investor's risk.

The most complete study including risk in this field is that of [4] which studies the performance of the obtained rules minimizing risk.To this aim it applies different risk measures (among which is Sharpe's ratio), but, leaving

[4] Strategy which is used as a benchmark in this field and which consists in the return which an investor would have obtained if they had bought at the beginning of the reference period and sold at the end. In this way the efficiency of the trading undertaken can be measured.

aside return as an aim and obtaining very similar results to those published maximizing return.

It is the case of [5] where the relation between risk and return in the evolution of the rules is taken into account, using the drawdown (longest losing streak in the period of study) as a measurement of risk but obtaining very varied results.

Maximization of return, which is the objective function of most works, leads to trading rules with a very high risk which in the medium/long term may generate losses, also the rules whitch only considere de level of risk cannot generate good returns either, [6]. Therefore, we consider it fundamental to contemplate the relationship between risk and return in the training of the rules

This work proposes the extension of the methodology presented in [6] to a group of different assets belonging to Spanish *IBEX35* index.

To check the efficiency of the methodology, the obtained results will be compared with those obtained applying the habitual methodologies in the literature.

The work is structured as follows: in Section 2 we describe briefly our methodology. In Section 3 a comparative study between the results for the *S&P500* index and the new assets presented in the present work will be included. The work finishes with conclusions and future work in Section 4.

2 A methodology for generating technical trading rules

The methodology based on genetic algorithms for the automatic generation of trading rules presented in [6] is composed of two parts:

- An algorithm for the search of trading rules of stock market assets in the medium/long term, based on *GAP*s [7]. The design steps of this algorithm appear in Sections 2.1, 2.2 and 2.3.
- An incremental training technique defined in [6].

The result of the search carried out by the *GAP* algorithm will be a trading rule which provides signs of purchase/sale about a specific asset.

2.1 Description of the trading rules. Fenotype

The trading rules generated by the algorithm are represented as a decision tree composed of arithmetical operators: $+$, $-$, $*$,/, $a^{(1/2)}$, log and a^b; comparative operators: $=$, $<$, $<=$, $>$, $>=$; logical operators: and / or; technical stock market indicators which may have one or two parameters, integer or real, which will be tree leaf nodes (rule).

A trading rule is applied for each observation of the data series, whether it is training or test. As a result of this application, a *TRUE* value (which indicates purchase) or a *FALSE* value (which indicates sale) is obtained. Given that we always invest all the available capital, if we have taken a purchase position, and the rule returns *TRUE*, we cannot increase the investment, therefore we will do nothing. Likewise, whenever we adopt a sale position we will sell all the capital, so if after a sale the rule returns *FALSE*, we cannot sell more.

2.2 Genetic Formulation. Genotype and crossover and mutation operatores

Each individual GAP will be formed by:

- A decision tree (GP) with limited height of 10 and limited size of 50 nodes.
- A GA chain with length of $s \cdot (n+1)$, being the length of each segment of the chain and the number of technical indicators.

The GA chain will be divided into $n+1$ segments of s length. The first segment is dedicated to real coefficients for the arithmetical operations and each of the n following segments will contain the suitable parameters for each type of technical indicator. In the implementation developed for this work will be 3.

We have selected a cross operator which crosses either the GP part or the GA chain with the same probability. For the GP part a one-point cross operator [8] will be employed and for the GA part a uniform arithmetical cross operator is used [9]. The selection method for the nodes to be crossed is uniform sampling without replacement. In the case of the mutation operator a coin is tossed to decide whether the GP part or the GA is selected to be mutated.

2.3 Evaluation function

In this work we have used the yearly Sharpe ratio as a risk measurement, [10]. This index was developed by Sharpe [11] and it measures the relationship between the return and its historic volatility. That is, between the return and the risk assumed to achieve it. The greater the value of this index, the lower the assumed risk, as the annual returns of this rule will be more homogeneous.

GAP evaluation function will take into account both return and risk. According to this, two objectives are defined, namely $Fitness^{minrisk}$ and $Fitness^{maxreturn}$. A priori, it could be thought that the suitable Fitness is a Pareto multiobjective evaluation function[5], [12], [13]. However, the preliminary tests carried out showed a divergent evolution of both objectives, obtaining high return and high levels of risk.

For that reason, a sequential optimization of the objectives was chosen, in which risk is first minimized to an intermediate generation (C) and from then on return is maximized. The first objective to be optimized will be $Fitness^{minrisk}$. During this phase, we will minimize the level of risk assumed by the rules, maximizing its Sharpe ratio. The maximum Sharpe ratio obtained until the generation C (RS_{max}) will be assumed as the risk threshold for the second phase, during which the optimization of the second objective, $Fitness^{maxreturn}$, will be carried out. That is, if during the first phase an RS_{max} of 2.5 is obtained, in the second phase all the rules whose Sharpe ratio is inferior to 2.5 will be discarded.

The greater C, the greater RS_{max} will be and, therefore, the risk level will be lower.

[5] The chosen multi-objetive algorithm was the SPEA - Strength Pareto Evolutionary Algorithm, one of the earliest technique.

In practice, we will call S the number of generations during which risk is minimized and R the number of generations during which return is maximized, maintaining RS_{max} as the level of risk. Varying the values of S and R we will carry out different combinations of return-risk and we will see what the influence is of such variation on the return of the generated rules. By taking into account both factors in the training of the rules, we expect to obtain rules with low risk and high return.

The total number of generations of the algorithm will be $G = S + R$.

According to the values of S and R we will define three fitness functions:

- $Fitness^{return}$: $S = 0$, $G = R$; Only return is taken into account as an objective.
- $Fitness^{risk}$: $R = 0$, $G = S$; Only risk is taken into account as an objective.
- $Fitness^{return\_risk}$: $G = S + R$; Function proposed in this work, where both return and risk are taken into account.

considering $Fitness^{return}$ and $Fitness^{risk}$ have been proposed in the literature in [1] and in [4] respectively. Here, they are expressed in terms of the proposed fitness $Fitness^{return\_risk}$.

2.4 Incremental training

In this work we propose a standard to homogenize the size of the training and testing periods, based on the incremental training technique, which consists in: a) for training we will use periods of ten years. We consider that this number of years provides a great deal of information to the algorithm (to the technical indicators); b) as a test period we use lengths of one year, due to the fact that the stock market is very variable and we consider that a rule may lose effectiveness in a longer period of time.

Each year a new rule is generated, considering the ten previous years (the first year of the training set is eliminated and the year prior to the test set is added) and in this way the information which is used for the evolution of the rules is updated and adapted to the market variations.

Incremental training permits a better adjustment of the rules to the test period, increasing the RMA. However, in standard training the generated rule obtains a lower RMA in the test period. We have taken as a measure of overfitting the expression:

$$SE = \frac{RMA(Training)}{RMA(Test)}$$

According to the results shown in the next section, the level of overfitting is markedly inferior in the tests carried out using incremental training compared with those using standard training. This is equivalent to an SE value close to 1.

3 Numerical Results

The tests have been carried out using as a training period the closing prices of the index and assets [6] from 06/01/1988 until 31/12/1997 (ten years) and as a test period from 02/01/1998 until 30/12/2005 (eight years). Each test is repeated ten times. In other words, ten rules are obtained and the mean of the results for each rule is calculated.

The algorithm proposed in this work has been implemented under *Java* with the help of the development environment of *Keel* software [14].

The trading parameters and *GAP* configuration are the same as the ones used in [6].

3.1 Results for the new assets

This work tries to prove the validity of the methodology presented in [6] for different assets from a new market, so a group of representative assets of the Spanish *IBEX35* index are selected: *TEF*, *BBVA* and *BSCH*.

This section compares the results of applying proposed methodology in three variants ($MP_{1,2,3}$)[7], incremental training and grammar directed to the new assets with classical methologies ($MC_{1,2}$[8])

Table 1. Comparative study of applying proposed methodology MP_3 and its variants $MP_{1,2}$ with classical methologies $MC_{1,2}$ on S&500 index (S=30, R=20) and TEF (S=10, R=20). Being r_+: percentage of profitable rules, RS: Sharpe ratio, RMA: percentage of mean annual return, RT: percentage of period return ($\frac{Capital_{final} - Capital_{initial}}{Capital_{initial}}.100$), SE: Measurement of over-fitting (—RMA(Training)/RMA(Test)—)

	Train			Test				Train			Test			
	$S\&P500$							TEF						
	$\bar{r}+$	RS	$R\bar{M}A$	$\bar{r}+$	$R\bar{M}A$	$R\bar{T}$	$S\bar{E}$	$\bar{r}+$	RS	$R\bar{M}A$	$\bar{r}+$	$R\bar{M}A$	$R\bar{T}$	$S\bar{E}$
MC1	100	0,55	27,68	60,00	-6,09	-6,09	1,22	100	0,47	88,48	40,00	-0,65	-0,65	1,01
MC2	100	2,34	7,54	40,00	-14,46	-14,46	2,91	100	1,52	7,59	10,00	-4,14	-4,14	1,54
MP1	100	1,62	10,33	58,80	3,12	26,87	0,69	100	1,44	27,39	50,00	5,60	40,14	0,79
MP2	100	1,86	9,43	70,00	4,92	46,21	0,47	100	1,36	29,47	47,14	6,30	42,70	**0,78**
MP3	100	1,92	11,33	68,75	**7,30**	**72,30**	**0,36**	100	1,24	36,52	52,86	**7,21**	**53,54**	0,80

[6] Obtained through the program *Visual Chart*^{TM} ©AG Mercados. See www.visualchart.com.

[7] MP_1: fitness^{risk}, incremental training and non grammar directed ;MP_2: $fitness^{risk}$, incremental training and grammar directed, MP_3: $fitness^{risk\_return}$

[8] MC_1: return maximization, not-incremental training and non grammar directed;MC_2: risk minization, not-incremental training and non grammar directed

Tables 1 and 2 show the results obtained for S&P500 index and the new assets *TEF(Telefónica)*, *BBVA* y *BSCH* respectively.

All the cases of the proposed methodology, $MP_{1,2,3}$, overpass highly the return ($\bar{RMA}$) obtained by the classical ones, MC_1 y MC_2 in the $Test$ period for each new asset. This improvement is due to the incremental adding to methodologies MP of the new techniques presented in work [6]: incremental training, grammar directed trading rules and fitness^{return_risk}. Also, the application of the proposed methodology causes a marked decrease of over-fitting ($\bar{SE}$) with regard to MC_1 y MC_2. Also a decrease of risk (see $\bar{RS}$) can be observed, in all the methodology compared with MC_1, except in some cases in which the level of risk is lightly increased to get profitable rules (see Tables 1,2 - assets *TEF* and *BBVA* - row MP_3).

It can be said that the final proposed methodology MP_3 enables to adjust the suitable risk level to get the major return for each asset. This optimization of the pair return-risk is the main objective of the work [6].

Table 2. Comparative study of applying proposed methodology MP_3 and its variants $MP_{1,2}$ with classical methologies $MC_{1,2}$ on $BBVA$ ($S = 30$, $R = 10$) and $BSCH$ ($S = 20$, $R = 30$). Being r_+: percentage of profitable rules, RS: Sharpe ratio, RMA: percentage of mean annual return, RT: percentage of period return ($\frac{Capital_{final} - Capital_{initial}}{Capital_{initial}}.100$), SE: Measurement of over-fitting (—RMA(Training)/RMA(Test)—)

	Train			Test				Train			Test			
	$BBVA$							$BSCH$						
	$\bar{r}+$	$\bar{RS}$	$\bar{RMA}$	$\bar{r}+$	$\bar{RMA}$	$\bar{RT}$	$\bar{SE}$	$\bar{r}+$	$\bar{RS}$	$\bar{RMA}$	$\bar{r}+$	$\bar{RMA}$	$\bar{RT}$	$\bar{SE}$
MC1	100	0,48	140,25	0,00	-5,55	-5,55	1,03	100	0,57	136,40	0,00	-6,07	-6,07	1,04
MC2	100	1,26	24,75	80,00	2,15	2,15	0,91	100	1,09	18,16	90,00	4,61	4,61	0,74
MP1	100	1,37	21,84	51,43	3,19	22,06	0,85	100	1,22	28,87	50,00	3,70	19,91	0,87
MP2	100	1,35	20,25	50,00	3,73	26,47	0,81	100	1,45	19,11	58,57	4,63	34,93	**0,75**
MP3	100	1,31	22,40	50,00	**6,04**	**45,22**	**0,73**	100	1,47	28,53	62,50	6,76	**64,14**	0,76

3.2 Comparative study with Buy&Hold strategy

In Table 3 a relation is shown of percentage of period return during all the test period, obtained applying MP_3 and *Buy&Hold* strategies for each new asset. It can be observed that in every asset but TEF, the proposet methodology obtains higher return than *Buy&Hold* strategy.

The evolution of the TEF asset during the reference period was so rare, because of its high profitability. This situation was due to enterprise strategies like capital increase, and also the main reason was that this asset was the most traded asset in the *IBEX35* index during the reference period.

It is very hard for an automatic trading system to overpass such a high profit [2], because the number of purchase-sale operations would be very high. By other hand this is an adventage of the trading system, since it's not compulsary to keep the capital invested during all the reference period (eight years in our study).

Table 3. Comparative study respect *Buy&Hold* strategy. *RT*: percentage of period return ($\frac{Capital_{final}-Capital_{initial}}{Capital_{initial}}.100$)

Asset	*Buy&Hold RT*	MP_3 *RT*
S&P500	27,10%	72,30%
TEF	100,41%	53,54%
BBVA	23,45%	45,22%
BSCH	53,28%	64,14%

4 Conclusions and Future work

Incremental training diminishes over-fitting and this increases the return of the rules, especially when applied combined with the minimization of risk. However, we are not training the rules so it is possible to generate higher returns.

In this work we prove that previously presented methodology can be used to obtain a trading rule for other kind of assets different from the one selected for the original methodology (*S&P500* index). In the section 3.2 it can be seen that our methodology obtains quite good profits for the new assets, only lightly lower than $S\&P500$ profit. Also, the profits overpass the *Buy&Hold* strategy profit for all the asset but TEF.

We believe that a variant of the methodology proposed here can be applied to an asset of the derivative market (for example futures on $IBEX35$). This will allow us to contrast the results obtained in a totally different market. This type of assets are less known by the general public and are normally only used by professional investors or by investment funds for hedging operations. However, they have several advantages which make them ideal for trading: lower operational costs, possibility of obtaining return in bear markets and less leverage. The operation with derived assets, especially with futures, permits the carrying out of operations on a nominal amount far above the capital initially invested, which in the case of futures is limited to the deposit of a quantity as a guarantee. In this way, a risk is being assumed proportional to the nominal value of the operation and not to the quantity effectively invested, which gives rise to its high degree of leverage. Financial futures possess a high financial leverage as they offer the possibility of obtaining high return without the need for carrying out an initial investment except for the deposit of a guarantee.

By other hand, the proposed methodology can be transformed to a $GFRBS$ (Genetic Fuzzy Rule Base System) [15] [3] using the $MOGUL$ methodology [16]. The main novelty in this genetic fuzzy trading system will be the use of the risk like one objective and an incremental training.

Acknowledgements

This work has been carried out with the support of the Ministerio de Ciencia y Tecnologia and the FEDER funds, within the project TIN2008-06681-C06-04.

References

1. Allen, F., Karjalainen, R.: Using genetic algorithms to find technical trading rules. Journal of Financial Economics (51) (1999) 245–271
2. Potvin, J.Y., Soriano, P., Valle, M.: Generating trading rules on the stock markets with genetic programming. Computers and Operations Research (31) (2004) 1033–1047
3. Chavarnakul, T., Enke, D.: A hybrid stock trading system for intelligent technical analysis-based equivolume charting. Neurocomputing **72**(16-18) (2009) 3517 – 3528 Financial Engineering; Computational and Ambient Intelligence (IWANN 2007).
4. Neely, C.J.: Risk-adjusted, ex ante, optimal, technical trading rules in equity markets. Technical report, Federal Reserve Bank of St. Louis. (2001)
5. O'Neill, M., Brabazon, A., Ryan, C.: Forecasting market indices using evolutionary automatic programming. a case study. In: Genetic Algorithms and Genetic Programming in Computational Finance, University of Limerick (Ireland) and University College Dublin (Ireland) (2002)
6. Fernandez, M.E., de la Cal, E.A., Quiroga, R.: Improving return using risk-return adjustment and incremental training in technical trading rules with gaps. Applied Intelligence **On-line** (2009) 1 – 14
7. Howard, L., D'Angelo, D.: The ga-p: a genetic algorithm and genetic programming hybrid. IEEE Expert (1995) 11–15
8. Koza, J.: Genetic Programming: On the programming of computers by means of Natural Selection and Genetic. MIT press (1992)
9. Michalewicz, Z.: Genetic Algorithms + Data Structures = Evolution Programs. Springer-Verlag (1992)
10. Xufre Casqueiro, P., Rodrigues, A.: Neuro-dynamic trading methods. European Journal of Operational Research (175) (2006) 1400–1412
11. Sharpe, W.F.: Mutual fund performance. Journal of Business. Supplement on Security Prices (39) (January 1966) 119–38
12. Coello-Coello, C., Veldhuizen, V., Lamont: Evolutionary Algorithms for solving Multi-objective Problems. Kluwer (2002)
13. Elaoud, S., Loukil, T., Teghem, J.: The pareto fitness genetic algorithm: Test function study. European Journal of Operational Research (177) (2007) 1703–1719
14. Alcal-Fdez, J., Snchez, L., Garca, S., del Jesus, M., Ventura, S., Garrell, J., Otero, J., Romero, C., Bacardit, J., Rivas, V., Fernndez, J., Herrera, F.: Keel: A software tool to assess evolutionary algorithms to data mining problems. Soft Computing - A Fusion of Foundations, Methodologies and Applications (2008 Online)
15. Ng, H., K.P., L., S.S., L.: Incremental genetic fuzzy expert trading system for derivatives market timing. In: IEEE International Conference on Computational Intelligence for Financial Engineering, Hong-Kong (2003) 421–428
16. Cordn, O., Jesus, M.J.D., Jesus, M.J.D., Herrera, F., Herrera, F., Lozano, M., Lozano, M.: Mogul: A methodology to obtain genetic fuzzy rule-based systems under the iterative rule learning approach. International Journal of Intelligent Systems **14** (1998) 1123–1153

Corrections

This section includes the answer to reviewers comments:

4.1 Review1

- Question1: The Methodology Section will be reorganized to undertand better the problem. Answer1: InCremental training step is included to clarify this stage of the proposed methodology.
- Question2: Including references to Genetic Fuzzy Rule Base System and MOGUL Methodology will be more explicity the future work. Answer2: References have been included.
- Question3: The references will be organized similarat Springer Verlag Format. Answer3: bibliographystyle label has been modified.

4.2 Review2

Some small observations:

- Question1: don't use subsections in introduction. Answer1: The subsections were deleted.
- Question2: rename section 2. Anwser2: The new name is "A methodology for generating technical trading rules"
- Question3: modify the sentence beginning with: ? on which...? page IV. Answer3: on which is replace by considering.
- Question4: citations in brackets [citation]. Answer4: bibliographystyle label has been modified.
- Question5: Paradoxically ? change the word or change the phrase. Answer5: Paradoxically is eliminated.
- Question6: numbers for the references. Answer6: bibliographystyle label has been modified.
- Question7: write Tables with capital T (ex. Table 2). Answer7: all references to table x has replaced with capitalized version Table x
- Question8: to many footnotes... please write some footnotes as sentences in the text (ex. 4, 10) ; (5 as a text in a parenthesis). Question8: Footnote 4. We consider that this footnote must not be in the text because it contains too much information for an introduction; Footnote 5. It's included in the text. Foonote 10. It's included in the text.
- Question9: rearrange the notations, formulas and abbreviations using italics. Answer9: All formula and abbreviation have been rewritten in italic.
- Question10: Consistency in notations . Answer10: Some notations where corrected, e.g. Fitness sub/super-index.
- Question 11: comma, next to the word ? section 2. Answer11: A black was inserted.
- Question 12: rearrange text in section 2.2 ? last sentence. Answer12: A new explanation is included for the mutation operator.

- Question 13: bold the best results in tables. Answer13: The best results in each column is bolded.
- Question 14: center Table 3. Answer14: Table 3 was centered.