Portfolio Construction Using Argumentation and Hybrid Evolutionary Forecasting Algorithms

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Abstract. In the current contribution, an application for constructing mutual fund portfolios is presented. This approach comprises of several Intelligent Methods, namely an argumentation based decision making framework and a hybrid evolutionary forecasting algorithm which combines Genetic Algorithms (GA), MultiModel Partitioning (MMP) theory and Extended Kalman Filters (EKF). Specifically, the argumentation framework is employed in order to develop mutual funds performance models and to select a small set of mutual funds, which will compose the final portfolio. On the other hand, the hybrid evolutionary forecasting algorithm is applied in order to forecast the market status (inflating or deflating) for the next investment period. The knowledge engineering approach and application development steps are also presented and discussed.

Keywords. Portfolio Construction, Mutual Funds, Intelligent Methods, Argumentation, Forecasting, Hybrid Evolutionary Algorithms

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1 INTRODUCTION

Portfolio management [21] is concerned with constructing a portfolio of securities (e.g., stock, bonds, mutual funds [32], etc.) that maximizes the investor's utility. In a previous study [34], we constructed mutual fund (MF) portfolios using an argumentation based decision making framework. We developed rules that characterize the market and different investor types policies using evaluation criteria of fund performance and risk. We also defined strategies for resolving conflicts over these rules. Furthermore, the developed application can be used for a set of different investment policy scenarios and supports the investor/portfolio manager in composing efficient MF portfolios that meet his investment preferences. Traditional portfolio theories ([21], [30], [31]) have been based on unidimensional approaches that do not fit to the multidimensional nature of risk ([8]), and they do not capture the complexity presented in the data set. In [34], this troublesome situation was resolved by the high level of adaptability in the decisions of the portfolio manager or investor, when his environment is changing and the characteristics of the funds are multidimensional, that was demonstrated by the use of argumentation.

Argumentation was selected among a number of different approaches as it: (a) allows for decision making using conflicting knowledge, (b) allows defining non-static priorities between arguments, and (c) the modularity of its representation allows for the easy incorporation of views of different experts. Traditional approaches such as statistical methods need to make strict statistical hypothesis, multi-criteria analysis methods need significantly more effort from experts, and neural networks require increased computational effort and are characterized by inability to provide explanations for the results.

Our study showed that when taking into account the market context, the results would be better if we could forecast the status of the market of the following investment period. In order to achieve this goal we employed a hybrid system that combines Genetic Algorithms (GA), MultiModel Partitioning (MMP) theory and the Extended Kalman Filter (EKF). A general description of this algorithm and its application in linear and non-linear data is discussed in [4], while the specific version used in this contribution is presented in [1], where its successful application to non-linear data is also presented. This algorithm captured our attention because it had been successfully used in the past for accurately predicting the evolution of stock values in the Greek market (its application on economic data is presented in [4]). Moreover, there is a lot of work on hybrid evolutionary algorithms and their application on many difficult problems has shown very promising results [9]. The problem of predicting the behavior of the financial market is an open problem and many solutions have been proposed ([21], [22], [25], [34]). However, there isn't any known algorithm able to identify effectively all kinds of behaviors. Also, many traditional methods have been applied to the same problem and the results obtained were not very satisfactory. There are two main difficulties in this problem, firstly the search space is huge and, secondly, it comprises of many local optima. We chose to apply a hybrid evolutionary system to this problem because Evolutionary Algorithms comprise a global forecasting technique, in the sense that a single formula is sought that allows forecasts of future entries in any series generated by the process—starting at any point in time. In this way, they perform well in cases where the search space is huge and/or comprises of many local optima.

In this contribution, we present the new portfolio construction application resulting from the combination of argumentation with hybrid evolutionary systems along with the obtained results.

The rest of the paper is organized as follows: Section two presents an overview of the concepts and application domain knowledge along with a presentation of the data set that we use. Section three outlines the main features of the proposed argumentation based decision-making framework and the developed argumentation theory. The forecasting hybrid evolutionary system is presented in section four, followed by section five, which presents the developed application and discusses the obtained empirical results. Finally, section six summarizes the main findings of this research and discusses its added value compared to different approaches in the past.

2 DOMAIN KNOWLEDGE

This section firstly presents the sources of the data that we used for our study. Subsequently, it describes the criteria (or variables) used for creating portfolios and the knowledge on how to use these criteria in order to construct a portfolio.

2.1 The Sample Data Set

The sample used in this study is provided by the Association of Greek Institutional Investors and consists of daily data of domestic equity mutual funds (MFs) over the period January 2000 to December 2007. Daily returns for all domestic equity MFs are examined for this eight-year period. At the end of 2007, the sample consisted of 80 domestic equity MFs. Nevertheless, not all MFs have been in operation for the whole eight-year time period of the analysis. Therefore, in order to eliminate the effect that could be caused by the fact that not all MFs were in operation for the same period, it was decided to consider only the ones for which complete data were available for each sub-period that the calculations were made.

For the application of the proposed methodological framework, further information is derived from the official web pages of the Athens Stock Exchange (www.ase.gr) and the Alpha Bank of Greece (www.alpha.gr), regarding the return of the Athens stock exchange market and the return of the three-month Treasury bill respectively. This information is very important as the variations of the returns in the ASE-GI, (Athens Stock Exchange-General Index) are expressed through the variation of the prices of the stocks taking also into account the fluctuations and the risk of the financial environment. Furthermore, the three-month Treasury bill is a risk-free asset, and constitutes the benchmark where the return of a MF or another risky investment is compared with.

2.2 Evaluation criteria

The proposed framework is based on five fundamental criteria, which represent basic characteristics of the examined funds. These characteristics of the examined funds refer to different performance and risk variables. The return variables are measuring the expected outcome of the investment in the MFs, while the risk variables are measuring the uncertainty about the outcome of the investment. These criteria are the following: (1) the return of the funds, (2) the standard deviation of the returns, (3) the beta coefficient, (4) the Sharpe index, and (5) the Treynor index. These variables are frequently used in portfolio management research area (see Table 1).

Table 1 Representative bibliography references of the examined criteria

Criteria	References
(1) Fund’s return	[6], [33], etc.
(2) Standard deviation of the returns	[19], [13], [12], etc.
(3) beta coefficient	[14], [33], etc.
(4) Sharpe index	[32], [16], etc.
(5) Treynor index	[36], [29], etc.

A brief description of these criteria follows. The return of the funds is the actual value of return of an investment defined by the difference between the nominal return and the rate of inflation. This variable is based on the net price of a fund. At this point, it is very important to mention that transaction costs such as management commission are included in the net price. Frond-end commission and redemption commission fluctuate depending on the MF class and in most cases are very low. The standard deviation is used to measure the variability of the fund's daily returns, thus representing the total risk of the fund. The beta coefficient (β) is a measure of fund's risk in relation to the capital risk. The Sharpe index [32] is a useful measure of performance and is used to measure the expected return of a fund per unit of risk, defined by the standard deviation. The Treynor index [36] is similar to the Sharpe index except that performance is measured as the risk premium per unit of systematic (beta coefficient) and not of total risk. The exact formulas by which these criteria are calculated are presented on Table 2.

On the basis of the argumentation framework for the selection of a small set of MF, which will compose the final multi-portfolios, the examined funds are clustered in three groups for each criterion for each year. For example, we have funds with high, medium and low performance for the return on funds variable, the same for the other criteria.

The aforementioned performance and risk variables visualize the characteristics of the capital market (bull or bear) and the type of the investor according to his investment policy (aggressive or moderate). Further information is represented through variables that describe the general conditions of the market and the investor policy (selection of portfolios with high performance per unit of risk).

The general conditions of the market are characterized through the development of funds which have high performance levels (high return on funds). Regarding the market context, in a bull market, funds are selected if they have high systematic or total risk. On the other hand, in a bear market, we select funds with low systematic and total risk. An aggressive investor is placing his capital upon funds with high performance and high systematic risk. Accordingly, a moderate investor selects funds with high performance and low or medium systematic risk. Some types of investors select portfolios with high performance per unit of risk. Such portfolios are characterized by high Sharpe ratio and high Treynor ratio.

Table 2. Criteria used

Criteria	Formulas	Variables definitions
(1) Fund's return	$R_{pt} = \frac{NAV_t + DIST - NAV_{t-1}}{NAV_{t-1}}$	▪ R_{pt} = return of MF in period *t*, ▪ NAV_t = closing net asset value of the fund on the last trading day of the period *t*, ▪ NAV_{t-1} = closing net asset value of the fund on the last trading day of the period *t-1*, ▪ $DIST_t$ = income and capital distributions (dividend of the fund) taken during period *t*
(2) Standard deviation of the returns	$\sigma = \sqrt{\frac{1}{T}\sum(R_{pt} - \overline{R}_{pt})^2}$	▪ σ = standard deviation of MF in period *t*, ▪ $\overline{R}_{pt}$ = average return in period *t*, ▪ T = number of observation (days) in the period for which the σ is being calculated
(3) beta coefficient	cov (R_{pt}, R_{Mt}) / var (R_{Mt})	▪ R_{Mt} = return of market portfolio (Athens Stock Exchange) in period *t,* ▪ cov (R_{pt}, R_{Mt}) = covariance of daily return of MF with market portfolio, ▪ var (R_{Mt}) = variance of daily return of market portfolio
(4) Sharpe index	$(R_{pt} - R_{ft}) / \sigma$	▪ R_{ft} = return of treasure bill in period *t*
(5) Treynor index	$(R_{pt} - R_{ft}) / \beta$	

3 ARGUMENTATION-BASED DECISION MAKING

In this section we firstly present the argumentation framework that we used and then we describe the domain knowledge modeling.

3.1 The Argumentation Framework

Autonomous agents, be they artificial or human, need to make decisions under complex preference policies that take into account different factors. In general, these policies have a dynamic nature and are influenced by the particular state of the environment in which the agent finds himself. The agent's decision process needs to be able to synthesize together different aspects of his preference policy and to adapt to new input from the current environment. Such agents are the mutual fund managers.

In order to address requirements like the above, Kakas and Moraitis ([17]) proposed an argumentation based framework to support an agent's self deliberation process for drawing conclusions under a given policy.

Argumentation can be abstractly defined as the principled interaction of different, potentially conflicting arguments, for the sake of arriving at a consistent conclusion (see e.g. [27]). The nature of the "conclusion" can be anything, ranging from a proposition to believe, to a goal to try to achieve, to a value to try to promote. Perhaps the most crucial aspect of argumentation is the interaction between arguments. This means that argumentation can give us means for allowing an agent to reconcile conflicting information within itself, for reconciling its informational state with new perceptions from the environment, and for reconciling conflicting information between multiple agents through communication. A single agent may use argumentation techniques to perform its individual reasoning because it needs to make decisions under complex preferences policies, in a highly dynamic environment (see e.g. [17]). This is the case used in this research. In the following paragraphs we describe the theoretical framework that we adopted:

Definition 1. A **theory** is a pair $(\mathcal{T}, \mathcal{P})$ whose sentences are formulae in the **background monotonic logic** $(\mathcal{L}, \vdash)$ of the form $L \leftarrow L_1,\ldots,L_n$, where $L, L_1, \ldots, L_n$ are positive or negative ground literals. For rules in P the head L refers to an (irreflexive) higher priority relation, i.e. L has the general form $L = h\_p(rule1, rule2)$. The derivability relation, $\vdash$, of the background logic is given by the simple inference rule of modus ponens.

An **argument** for a literal L in a theory $(\mathcal{T}, \mathcal{P})$ is any subset, T, of this theory that derives L, $T \vdash L$, under the background logic. A part of the theory $\mathcal{T}_0 \subset \mathcal{T}$, is the **background theory** that is considered as a non defeasible part (the indisputable facts).

An argument attacks (or is a counter argument to) another when they derive a contrary conclusion. These are conflicting arguments. A conflicting argument (from $\mathcal{T}$) is admissible if it counter-attacks all the arguments that attack it. It counter-attacks an argument if it takes along priority arguments (from $\mathcal{P}$) and makes itself at least as strong as the counter-argument (we omit the relevant definitions from [17] due to limited space).

Definition 2. An agent's **argumentative policy theory** is a theory $T = ((\mathcal{T}, \mathcal{T}_0), \mathcal{P}_R, \mathcal{P}_C)$ where $\mathcal{T}$ contains the **argument** rules in the form of definite Horn logic rules, $\mathcal{P}_R$ contains **priority** rules which are also definite Horn rules with head $h\_p(r_1, r_2)$ s.t. $r_1, r_2 \in \mathcal{T}$ and all rules in $\mathcal{P}_C$ are also priority rules with head $h\_p(R_1, R_2)$ s.t. $R_1, R_2 \in \mathcal{P}_R \cup \mathcal{P}_C$. $\mathcal{T}_0$ contains auxiliary rules of the agent's background knowledge.

Thus, in defining the decision maker's theory we specify three levels. The first level ($\mathcal{T}$) defines the (background theory) rules that refer directly to the subject domain, called the *Object-level Decision Rules*. In the second level we have the rules that define priorities over the first level rules for each *role* that the agent can assume or *context* that he can be in (including a *default context*). Finally, the third level rules define priorities over the rules of the previous level (which context is more important) but also over the rules of this level in order to define *specific contexts*, where priorities change again.

3.2 The Decision Maker's Argumentation Theory

Using the presented argumentation framework, we transformed the criteria for all MFs and experts knowledge (§2) to background theory (facts) and rules of the first and second level. Then, we defined the strategies (or specific contexts) in the third level rules.

The goal of the knowledge base is to select some MFs in order to construct our portfolio. Therefore, our rules have as their head the predicate *selectFund/1* and its negation. We write rules supporting it or its negation and use argumentation for resolving conflicts. We introduce the *hasInvestPolicy/2*, *preference/1* and *market/1* predicates for defining the different contexts and roles. For example, John, an aggressive investor is expressed with the predicate *hasInvestPolicy(john, aggressive)*.

The knowledge base facts are the performance and risk variables values for each MF, the thresholds for each group of values for each year and the above mentioned predicates characterizing the investor and the market. The following rules are an example of the object-level rules (level 1 rules of the framework - $\mathcal{T}$):

r_1(Fund): selectFund(Fund) ← highR(Fund)

r_2(Fund): ¬selectFund(Fund) ← highB(Fund)

The *highR* predicate denotes the classification of the MF as a high return fund and the *highB* predicate denotes the classification of the MF as a high risk fund. Thus, the r_1 rule states that a high performance fund should be selected, while the r_2 rule states that a high risk fund should not be selected. Such rules are created for the three groups of our performance and risk criteria.

Then, in the second level we assign priorities over the object level rules. The $\mathcal{P}_R$ are the *default context rules* or level 2 rules. These rules are added by experts and express their preferences in the form of priorities between the object level rules that should take place within defined contexts and roles. For example, the level 1 rules with signatures r_1 and r_2 are conflicting. In the default context the first one has priority, while the bear market context reverses this priority:

R_1: h_p(r_1(Fund),r_2(Fund)) ← true

R_2: h_p(r_2(Fund),r_1(Fund)) ← market(bear)

Rule R_1 defines the priorities set for the default context, i.e. an investor selects a fund that has high return on investment (RoI) even if it has high risk. Rule R_2 defines the default context for the bear market context (within which, the fund selection process is cautious and does not select a high RoI fund if it has high risk).

Finally, in $\mathcal{P}_C$ (level 3 rules) the decision maker defines his strategy and policy for integrating the different roles and contexts rules. When combining the *Aggressive investor* role and *bear market* context, for example, the final portfolio is their union except that the aggressive investor now would accept to select high and medium risk MFs (instead of only high). The decision maker's strategy sets preference rules between the rules of the previous level but also between rules at this level. Relating to the level 2 priorities, the bear market context's priority of not buying a high risk MF, even if it has a high return, is set at higher priority than that of the general context. Then, the specific context of an aggressive investor in a bear market defines that the bear market context preference is inverted. See the relevant priority rules:

C_1: h_p(R_2, R_1) ← true

C_2: h_p(R_1, R_2) ← hasInvestPolicy(Investor, aggressive).

C_3: h_p(C_2, C_1) ← true

Thus, an aggressive investor in a bear market context would continue selecting high risk funds. In the latter case, the argument r_1 takes along the priority arguments R_1, C_2 and C_3 and becomes stronger (is the only admissible one) than the conflicting r_2 argument that can only take along the R_2 and C_1 priority arguments. Thus, the *selectFund(Fund)* predicate is true and the fund is inserted in the portfolio.

The problem with the above rules is that the facts *market(bear)* or (exclusive) *market(bull)* could not be safely determined for the next investment period. In the application version presented in [34] it was just assumed to remain the same as at the time of the investment. This strategy, however, produced quite poor results for this context if it should change in the next period.

4 FORECASTING THE STATUS OF THE FINANCIAL MARKET

One of the most prominent issues in the field of signal processing is the adaptive filtering problem, with unknown time-invariant or time-varying parameters. Selecting the correct order and estimating the parameters of a system model is a fundamental issue in linear and nonlinear prediction and system identification. The problem of fitting an AutoRegressive Moving Average model with eXogenous input (ARMAX) or a Nonlinear AutoRegressive Moving

Average model with eXogenous input (NARMAX) to a given time series has attracted much attention because it arises in a large variety of applications, such as time series prediction in economic and biomedical data, adaptive control, speech analysis and synthesis, neural networks, radar and sonar, fuzzy systems, and wavelets [15].

The forecasting algorithm used in this contribution is a generic applied evolutionary hybrid technique, which combines the effectiveness of adaptive multimodel partitioning filters and GAs' robustness [1]. This method has been first presented in [18]. Specifically, the a posteriori probability that a specific model, of a bank of the conditional models, is the true model, can be used as fitness function for the GA. In this way, the algorithm identifies the true model even in the case where it is not included in the filters' bank. It is clear that the filter's performance is considerably improved through the evolution of the population of the filters' bank, since the algorithm can search the whole parameter space. The proposed hybrid evolutionary algorithm can be applied to linear and nonlinear data; is not restricted to the Gaussian case; does not require any knowledge of the model switching law; is practically implementable, computationally efficient and applicable to online/adaptive operation; and, finally, exhibits very satisfactory performance as indicated by simulation experiments [4]. The structure of the hybrid evolutionary system used is depicted in Fig. 1.

The representation used for the genomes of the population of the GA is the following. We use a mapping that transforms a fixed dimensional internal representation to variable dimensional problem instances. Each genome consists of a vector **x** of real values $x_i \in \Re$, $i = 1, ..., k$, and a bit string **b** of binary digits $b_i \in \{0,1\}$, $i = 1, ..., k$. Real values are summed up as long as the corresponding bits are equal. Obviously, k is an upper bound for the dimension of the resulting parameter vector. We use the first $k/3$ real values for the autoreggressive part, the second $k/3$ real values for the moving average part, and the last $k/3$ real values for the exogenous input part. An example of this mapping is presented in Fig. 2. For a more detailed description of this mapping refer to [4]. In this specific implementation the number of genes comprising each genome of the GA equals to 12. Subsequently and according to our model, the first 4 real values are used for the autoreggressive part, the second 4 real values are used for the moving average part, and the last 4 real values are used for the exogenous input part.

At first, an initial population of m genomes is created at random (each genome consists of a vector of real values and a bit string). In this specific implementation the number of possible solutions that are evolved, that is the population size of the GA, equals to 20. As stated before, each vector of real values represents a possible value of the

NARMAX model order and its parameters. For each such population we apply an MMAF with EKFs and have as result the model-conditional probability density function (pdf) of each candidate model. This pdf is the fitness of each candidate model, namely the fitness of each genome of the population (Fig. 3).

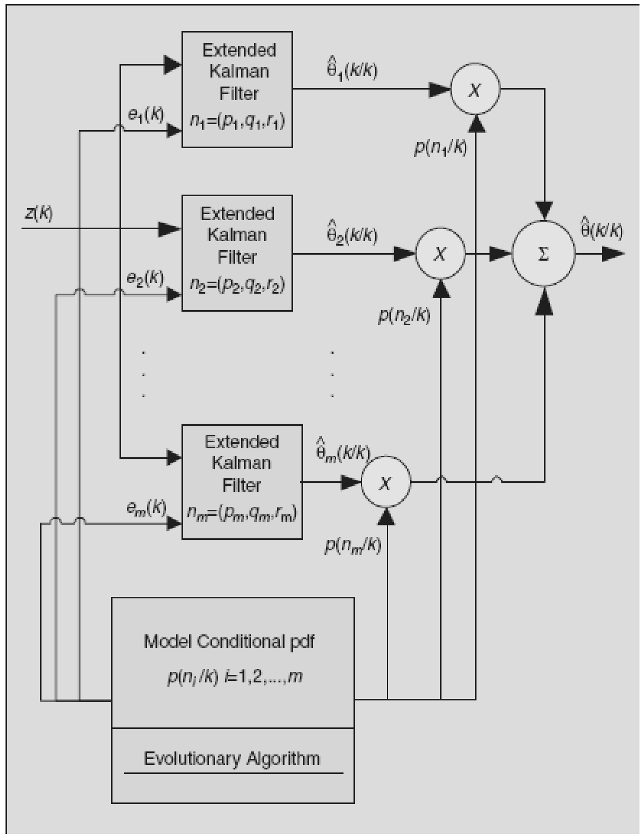

Fig. 1: The structure of the hybrid evolutionary system used for forecasting.

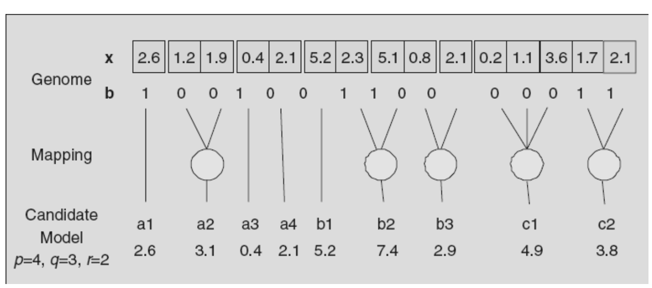

Fig. 2: Mapping from a fixed dimensional internal representation to a variable length NARMAX parameter vector. The resulting order is n(p, q, r) = (4, 3, 2).

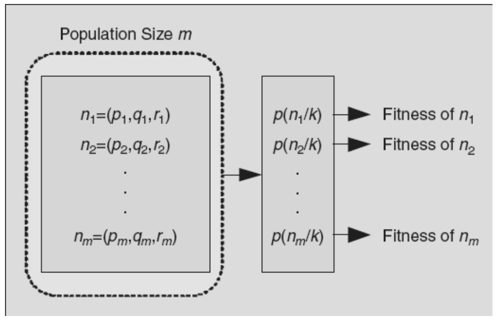

Fig. 3: The fitness of each candidate model is the model conditional pdf (m is the number of the extended Kalman filters in the multimodel adaptive filter).

The reproduction operator we decided to use is the classic biased roulette wheel selection according to the fitness function value of each possible model order [22]. As far as crossover is concerned, we use the one-point crossover operator for the binary strings and the uniform crossover operator for the real values [22]. For both crossover operators a probability equal to 0.9 was used. Finally, we use the flip mutation operator for the binary strings and the Gaussian mutation operator for the real values [22]. For both mutation operators a probability equal to 0.1 was used. Every new generation of possible solutions iterates the same process as the old ones and all this process may be repeated as many generations as we desire or till the fitness function has value 1 (one) which is the maximum value it is able to have as a probability. For a more detailed description of this hybrid evolutionary system refer to [4].

In this contribution we apply a slightly different approach compared to the one presented in [4]. In [4], at the algorithm's step where the value of the estimation (output) x of each filter is calculated, the past values of x that are used in order to estimate the next value of x are always taken from the estimation file (the file of all past values of x that have been estimated by the algorithm till this point). All these values are used in each generation in order to estimate the next value of the estimation (output) vector $\boldsymbol{x}$. The method presented in this contribution uses a different approach in order to estimate $\boldsymbol{x}$. At the algorithm's step where the value of x for each filter is calculated, the past values of x that are used in order to estimate the next value of x are smaller than the total length of the time series that has been estimated till this point. The length of past values used in each generation in order to estimate the next value of $\boldsymbol{x}$ equals to $n/2$, where n is the total length of the time series to be estimated. Every new value of x, estimated by the algorithm, is added to this time series of length $n/2$ and the oldest one is removed in order this time series to sustain a length of *n/2*. The value of *n/2* was not selected arbitrarily. We have conducted exhaustive experiments using many different values. The value of *n/2*, that has been finally selected, was the most effective one, that is, the one that resulted in the best prediction results. In this specific implementation the value of parameter *n* equals 30, that is 30 semesters are used as past values for forecasting, starting from the first semester of 1985. Of course, as stated before, every new value of *x* (status of the financial market for a specific semester), estimated by the algorithm, is added to this time series of length 30 and the oldest one is removed in order this time series to sustain a length of 30.

Thus, the hybrid evolutionary system presented in Fig. 1 is used in order to forecast the behavior of the financial market in relation to its current status. The market is characterized as bull market if it is forecasted to rise in the next semester, or as bear market if it is forecasted to fall. We used the percentage of the return of the Athens Stock Exchange index for each semester (in relation to the previous semester) starting from year 1985 to the years of our sample data (2000 to 2007). Our algorithm indicates a bull market if this percentage is forecasted to be positive or a bear market if it is forecasted to be negative. The algorithm performed very well considering that it could forecast the next semester market behavior with a success rate of 88.24% (15 out of 17 right predictions), as presented in Table 3.

One can argue, after studying the results presented in Table 3, that the forecasted values of change are far different from the actual values of the change of the financial market index. However, the algorithm is not applied in order to predict specific values of the financial market index. It is used, as stated above, in order to predict the next semester financial market behavior, which is the behavior of the financial market in relation to its current status (whether the financial market index of the current semester is higher or lower compared to the financial market index of the previous semester). Results presented in Table 3 demonstrate that the proposed forecasting algorithm achieves very satisfactory results in doing this.

5 THE PORTFOLIO CONSTRUCTION APPLICATION

In this section we firstly present the system architecture, i.e. the combination method for the argumentation decision making sub-system and the hybrid forecasting sub-system that resulted in a coherent application. Then we present the results of this combination.

Table 3: Results obtained after applying the presented forecasting algorithm in order to forecast the sign (positive or negative) of the return of the Athens Stock Exchange index for each semester (the rows with grey background indicate the failed forecasts).

Semester	RASE change (%)	Forecasted value
1st sem 2000	-26.751	5.552
2nd sem 2000	-15.706	-4.006
1st sem 2001	-19.112	-2.409
2nd sem 2001	-5.267	-2.989
1st sem 2002	-14.822	-0.826
2nd sem 2002	-21.206	-2.334
1st sem 2003	6.468	-3.412
2nd sem 2003	21.190	1.025
1st sem 2004	1.535	3.391
2nd sem 2004	19.219	6.656
1st sem 2005	8.357	3.067
2nd sem 2005	19.204	1.343
1st sem 2006	0.831	3.118
2nd sem 2006	18.984	1.091
1st sem 2007	8.440	0.0125
2nd sem 2007	6.561	0.3002
1st sem 2008	-33.946	-0.002

5.1 System Architecture

The portfolio generation application is a Java program creating a human-machine interface and managing its modules, namely the decision making module, which is a prolog rule base (executed in SWI-prolog[†]) using the Gorgias[‡] framework, and the forecasting module, which is a Matlab[§] implementation of the forecasting hybrid system (see Fig. 4).

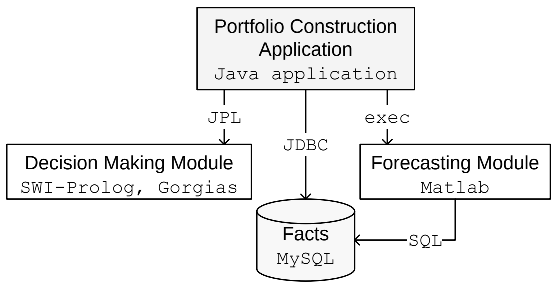

Fig. 4: System Architecture.

The application connects to the SWI-Prolog module using the provided Java interface (JPL) that allows for inserting facts to an existing rule-base and running it for reaching goals. The goals can be captured and returned to the Java program. The application connects to Matlab by executing it in a system shell. The matlab program writes the results of the algorithm to a MySQL[**] database using SQL (Structured Query Language). The application first executes the forecasting module, then updates the database, using JDBC (Java DataBase Connectivity interface) technology, with the investor profile (selected roles) and, finally, queries the decision making module setting as goal the funds to select for participation in the final portfolio. Thus, after the execution of the forecasting module the predicate

[†] SWI-Prolog offers a comprehensive Free Software Prolog environment, http://www.swi-prolog.org

[‡] Gorgias is an open source general argumentation framework that combines the ideas of preference reasoning and abduction, http://www.cs.ucy.ac.cy/~nkd/gorgias/

[§] MATLAB® is a high-level language and interactive environment for performing computationally intensive tasks, http://www.mathworks. com/products/matlab

[**] MySQL is an open source database, http://www.mysql.com

market/1 is determined as bull or bear and inserted as a fact in the rule base before the decision making process is launched. The reader can see in Fig. 5 a screenshot of the integrated system.

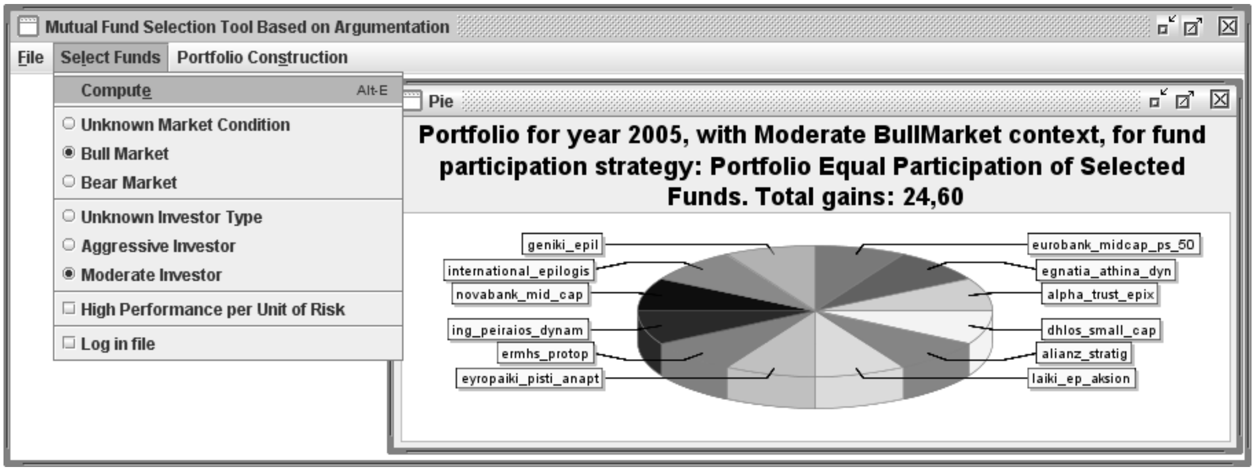

Fig. 5: A screenshot for portfolio generation for a scenario of a moderate investor in a bull market context.

5.2 System Evaluation

For evaluating our results we defined scenarios for all years for which we had available data (2000-2007) and for all combinations of contexts. That resulted to five simple scenarios (general, market, aggressive investor, moderate investor and high performance contexts) and five specific context scenarios (the two investor types combined with the market status, plus the two investor types combined with the high performance option, plus the market status combined with the high performance option) all run for eight years each. Each one of the examined scenarios refers to different investment choices and leads to the selection of different number and combinations of MFs.

Firstly, we use a limited range of these data (years 2000-2005) for comparing the hybrid approach presented in this paper to the previous argumentation-based approach ([34]). In Table 4 the reader can inspect the average *return on investment* (RoI) for the first six years (2000-2005) for all different contexts. The reader should notice that the table contains two RoI columns, the first ("Previous RoI") depicts the results before changing the system as they appeared in [34]. The second presents the results of upgrading the application by combining it with the hybrid evolutionary forecasting sub-system and by fixing the selected funds participation to the final portfolio. The latter modification is out of the scope of this paper but the reader can clearly see that it has greatly influenced the performance of all scenarios. Thus, Table 4, shows the added value of this contribution as the market context has become the most profitable in the "New RoI" column (8.17% RoI), while in the "Previous RoI" column it was one of the worst cases (3.72% RoI). Consequently, the specific contexts containing the market context have better results.

Table 4. Average RoI for six years. The New RoI column shows the gains after the evolutionary hybrid forecasting system's integration

Context type	*Context*	*Previous RoI (%)*	*New RoI (%)*
simple	general	3.53	6.86
role	aggressive	2.65	7.38
role	moderate	4.02	6.09
context	**market**	**3.72**	**8.17**
role	high performance	4.98	7.16
specific context	aggressive – market	3.56	7.92
specific context	moderate – market	4.72	6.08
specific context	aggressive - high p.	4.88	7.46
specific context	moderate - high p.	4.98	7.16
specific context	Market - high perf.	4.59	7.23
ASE-GI	RASE	6.75	

Moreover, Table 4 also shows the added value of our approach as the reader can compare our results with the return on investment (RASE) of the General Index of the Athens Stock Exchange (ASE-GI). According to the results of this table, the average return of the constructed portfolios for all contexts, except two, achieves higher return than the market index. The two cases where the constructed portfolios did not beat the market index are the moderate simple context and moderate-market specific context. This is, maybe, due to the fact that in these two contexts we have an investor who wishes to earn more without taking into account any amount of risk in relation to the variability which characterizes the conditions of the market during the examined period. This fact makes it very difficult to implement investment strategies that can help a fund manager outperform a passive investment policy. However, looking at Table 5, we find that for an investment range of eight years (2000-2007) all contexts are more profitable than the RASE.

Furthermore, in Table 5 we notice that in some specific contexts the results are more satisfying than the results obtained by simple contexts, while in others there is little or no difference. This means that by using effective strategies in the third preference rules layer the decision maker can optimize the combined contexts. Specifically, the *aggressive-high performance* specific context provides better results than both the simple contexts *aggressive* and *high performance* (the ones that it combines) and the *general* context. The *moderate-high performance* specific context's returns on investment are equal to the higher simple context's returns (*high performance*) while the *aggressive-market* specific context returns are closer to the higher simple context's returns (*market*).

Table 5. Resulting Portfolios for all contexts for all years and their returns compared to each other and to RASE. The values in the grey cells are those that were not successfully forecasted.

	Portfolios for contexts	**2007**	**2006**	**2005**	**2004**	**2003**	**2002**	**2001**	**2000**	**Avg**
simple contexts	General	-29,79	17,84	25,31	27,44	11,50	23,41	-25,31	-21,19	**3,65**
	Aggressive	-31,69	17,64	27,00	29,13	14,56	23,41	-28,65	-21,19	**3,78**
	Moderate	-29,43	18,19	24,60	26,17	8,05	23,41	-24,48	-21,19	**3,17**
	Market	-26,42	17,47	27,63	29,17	16,50	23,41	-24,69	-21,19	**5,24**
	HighPerfomance	-29,77	17,78	21,33	27,63	12,10	27,99	-24,76	-21,31	**3,87**
specific contexts	Aggressive Market	-29,06	17,47	27,63	29,17	15,04	23,41	-26,18	-21,19	**4,54**
	Moderate Market	-26,42	18,19	24,60	26,17	16,50	23,41	-24,69	-21,19	**4,57**
	Aggressive HighPerfomance	-29,77	17,84	23,90	27,44	11,50	27,99	-24,76	-21,31	**4,10**
	Moderate HighPerfomance	-29,77	17,78	21,33	27,63	12,10	27,99	-24,76	-21,31	**3,87**
	Market HighPerfomance	-29,77	17,78	21,33	27,63	12,10	27,99	-24,82	-21,31	**3,87**
	RASE (next year)	-38,97	15,95	19,95	29,71	20,42	27,38	-33,45	-23,53	**2,18**
	Forecasted as	Bear	Bull	Bull	Bull	Bear	Bull	Bear	Bull	

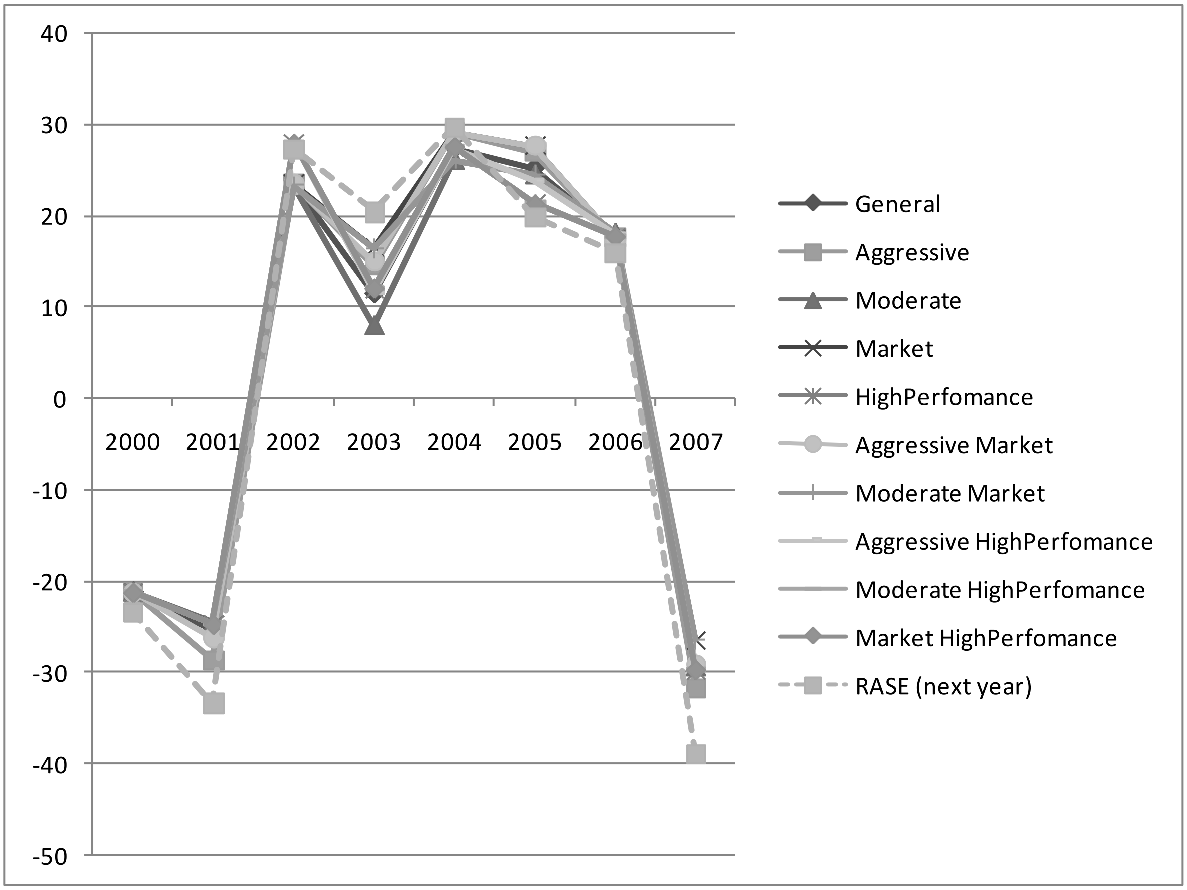

Fig. 6: Comparative RoIs of all contexts for each year.

Finally, in Fig. 6, we present the RoI of all contexts separately for each year. This view is also useful, as it shows that for two years, i.e. 2003 and 2004, RASE was greater than all our contexts RoI performance. This shows that our application, for the time being, performs better for medium term to long term investments, i.e. those that range over five years.

All in all, we evaluated our system in two major axes. Firstly, we compared its performance with a previously developed system [34], which also provides us with the benchmark scenarios (see Table 4). Then, we compared it with the performance of the Athens General Index (see Table 5). The benchmark data have been retrieved from the Athens Stock Exchange and such data have been used in the past for evaluating the performance of similar systems. For example, the systems presented in [5], [20] and [24] have been evaluated in comparison to the S&P 500, an index of the prices of 500 large cap common stocks actively traded in the two largest American stock markets, the

New York Stock Exchange and NASDAQ. Our eight-year performance data demonstrate that our system is useful for medium to long term investments (as in this time range it always provides a better performance than that of the ASE-GI).

6 RELATED WORK AND CONCLUSION

The objective of this paper was to present an artificial intelligence based application for the MF portfolio generation problem that combines two different intelligent methods, argumentation based decision making and a hybrid system that combines Genetic Algorithms (GA), MultiModel Partitioning (MMP) theory and the Extended Kalman Filter (EKF).

We described in detail how we developed our argumentation theory and how we combined it with the hybrid system to determine an important fact for the decision making process, i.e. the status of the financial market in the next investment period.

We chose argumentation as it allows for decision making using conflicting knowledge, thus different experts can express their knowledge without needing to be consistent with the opinions of the others. It allows to define nonstatic priorities between arguments, which means that the priorities of rules can depend on context. Finally, the modularity of its representation allows for the easy incorporation of views of different experts ([2]). Traditional approaches do not provide these benefits, on the contrary, they pose specific limitations. Statistical methods need to make a strict statistical hypothesis not allowing for flexibility ([2]). Multi-criteria analysis methods need significantly more effort from experts (e.g. Electre-tri, [38]) as they need to define criteria, weights, preference, indifference, veto thresholds, and profiles, leading, in some cases, to troublesome situations due to time constraints or the reluctance of the decision makers to actively contribute in a direct interrogation process managed by an expert analyst (see [11] for a complete comparison between decision support methods). Neural networks have also been used in the past (as in [25] for example), but they require increased computational effort and are characterized by their inability to provide meaningful explanations for the produced results ([35]). The reasons for using the selected argumentation framework ([17]) among others ([26]) are a) the well documented Gorgias open source library, and, b) the possibility for dynamic preference selection in different levels that allowed for the modular conception of the rules (the different experts could independently express their knowledge).

We chose GAs as they comprise a global forecasting technique, in the sense that a single formula is sought that allows forecasts of future entries in any series generated by the process—starting at any point in time. Local approximation schemes, on the other hand, deal only with data that lie in a close neighbourhood in the embedding space, and require separate computations for forecasts in different regions. Obviously, a conventional search for the actual equation of the data generating process is hopeless, since the dynamics underlying most data, especially financial series, are far too complicated. The usability of classical regression analysis techniques is also very limited. During the past decade various nonlinear techniques have been developed to accomplish the task of forecasting. The nearest neighbour technique ([10]) which requires massive amounts of data embeds the time series in a space of sufficiently high dimension and then seeks vectors in the historical series that are similar to the one that is to be predicted. Neural nets also use historical series that are similar to the one that is to be predicted, and the back propagation of errors, to fine tune a set of parameters, and thereby build a forecasting function that links past values of the time series with future values ([7]; [37]). Predictions based on radial basis functions ([23]) use global interpolation techniques and have proven useful in practice when only sparse data was available. Finally, wavelet analysis—like the Fourier transform—decomposes a time series into its basic components, thus allowing insight into its fine structure, and then uses a weighted sum of these wavelets for forecasting purposes ([28]).

The developed application allows a decision maker (fund manager) to construct multi-portfolios of MFs under different, possibly conflicting contexts. Moreover, for medium to long term investments, the returns on investment of the constructed portfolios are better than those of the General Index of the Athens Stock Exchange, while the best results are those that involve the forecasting of the financial market.

Our future work will be to develop a new rule base for the problem of determining when to construct a new portfolio for one of our investors. We will also make the application web-based so that it can get on-line financial data available from the internet for computing the decision variables and for allowing the investors to insert their profiles by filling on-line forms. Our aim is to be able to guarantee a better RoI than that of the RASE even for short term investments.

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