DECISION SUPPORT METHODOLOGIES IN FINANCE

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ABSTRACT

The increasing complexity of financial instruments traded in the Exchanges, the establishment of new markets and the improvement of real–time connections among them, all demand substantially powerful techniques for effective use by economic agents. To match the requirements of precision and timeliness of response many applications require extensive computational support as well as the use of tools as expert systems and neural networks is needed to handle symbolic data as professionals demand. The paper intends to present a review of the state–of–art on this topic, some ideas related to the pricing of primitive and derivative financial instruments and the importance that tools like neural machines can play. Moreover we deal with the pattern recognition problem which is typical of many financial situations, requires both large amount of computations and symbolic computation and can be solved through a neural network approach.

1. INTRODUCTION

Since the 80's, when new methodologies –ranging from artificial intelligence to parallel processing and more recently to neural networks –began to be used successfully in different areas for solving problems never solved before, many scientists and professionals working in the economic and financial field have started new researches along these topics.

The main reason for this interest is related to the increasing complexity of financial markets and of the economic system, and to the importance of having fast exchanges of reliable and accurate symbolic and numerical data.

Hence the necessity of exploring three domains.

The first relies on the knowledge of market behaviour, or how humans actually behave. Two approaches are available: the classical one, which leads to sophisticated econometric models due to some assumptions; the other, which is modeled through tools (artificial neural network) able to adapt to real human behaviour. Both approaches require very powerful processing, but distinct techniques.

The second domain is related to the necessity of knowing the fair price of assets, both primitive and derivative ones. Pricing the former financial instrument involves, besides the current value of the company, information derived from the market itself: this can suggest a valuable use of a connessionist approach coupled with the coded knowledge of an expert system. Pricing of derivative complex financial instruments can be a quite expensive computational task, expecially if we want to match the requirements of precision and timeliness of response which are essential for proper use.

Finally, decision makers are more and more often confronted with the need to handle symbolic data, for which conventional computations do not help. Hence the need for extensive use of such tools as expert systems.

Moreover, building expert systems becomes much more complex when the knowledge to code is fuzzy and this, again, can be accomplished by using the neural approach.

In the following, paragraph no.1 presents a review of the applications that, at our knowledge, have taken explicit advantage from the methodologies we mentioned above; paragraph no. 2 concerns pricing of primitive instruments and the important role that expert systems and neural networks can play; in the end we will express some final remarks and comments.

2. State–of–art

We illustrate here some of the main applications in the economic and financial areas, where the use of new methodologies has been crucial to get significant results.

2.1. Managing large portfolio of mortgage–backed securities (Zenios et al.)

Mortgage–backed securitites are created when mortgages from individual homeowners are pooled together. The issuing institution handles the transfer of funds from homeowners to investors retaining a service fee.

This kind of securities includes features of bonds and options; in particular the homeowners' ability to prepay the mortgage is a call option. In other words this means that the investor in mortgage–backed securities has written a call option to the mortgage borrower. Pricing the mortgage–backed security is therefore complicated by the fact that the mortgage borrower can refinance his mortgage at any point in time.

This kind of securities is quite well known in the USA while in Italy the lack of this market is essentially due to the fact that refinancing a mortgage is very inconvenient for the homeowner due to contract standards.

The management of a large portfolio of mortgage–backed securities has been modeled as a two stage, multiperiod stochastic programming problem and simulations over a period of thirty years have been carried out in acceptable time frames using a massively parallel computer.

Two main steps have been recognized in Zenios' model:

- estimation of the prepayment activity of homeowners based on historical data or on pricing the embedded prepayment option;
- evolution of interest rate based on stochastic models. What has been extensively shown in the Zenios' papers (Zenios 1991, Kang 1992, D'Ecclesia 92) is that this modeling framework, that integrates simulation with optimization under an uncertainty scenario, can be used in practice because of the recent developments in parallel processing.

All those applications which involve financial instruments whose returns are sensitive to interest rate movements, are good candidates for the modelling we mentioned above and therefore they could take substantial advantage of parallel processing methodology.

Among the possible applications, we can, for example, mention asset/liability management problems, the funding of insurance products or the structuring of long–term options.

2.2. Liability management of public institutions (Dempster et al.)

The work independently proposed by Dempster (Dempster 1988, 1989) is just in the framework illustrated above. Moreover it adds the expert system's methodology to make the decision maker's job easier.

The problem can be sketched as follows.

The decision maker's goal is to reduce costs and risks due to running into debt, in order to finance investment projects for public utility.

The decisions are influenced by factors that may vary according to chosen debt sources.

A strategic planning is often defined taking into account different possible scenarios and computing the consequent cost.

The system (which is named MIDAS) is organized in a structured and hierarchical way so that different techniques such as optimization, simulation and artificial intelligence, are used along the decision process stages. It includes, in an integrated environment, not only sophisticated optimization software (mixed integer linear programming, dynamic and stochastic programming) but also a coded knowledge of the expertise. Feedback operations on the user can also be carried out to check the alternatives proposed by the system.

The project is challenging and it requires the utilization of technologies which have to interact in a very coupled way (distributed or concurrent processing to simulate different scenarios together with inferential rules).

2.3. Solution of partial differential equations in more than one state variable

Partial differential equations (PDE for short) are involved in pricing most of the derivative financial instruments (we recall here that the well-known Black and Scholes formula comes from the analytic solution of a PDE).

Unfortunately in most cases, the PDEs are too complex and it is necessary to address numerical methods to solve them.

Numerical techniques for PDEs have been successfully and extensively used in many fields such as fluido-dynamics or strength-analysis requiring large computational effort.

On the contrary, in finance there are few papers (Brennan 1978, Boyle 1977, Geske 1985, Hull 1989) dealing with this matter. D'Ecclesia et al. (D'Ecclesia 1992) used a model involving a PDE with two state variables, i.e. short and long interest rates, plus the time variable on a thirty years simulation and it took hours on an IBM 3090 to be simulated.

Bertocchi (Bertocchi 1991) introduced a semi-explicit technique to solve a PDE model, involving one state variable and the time variable, which combines an higher stability than the explicit approach, with a reasonable speed in execution.

Specific algorithms for PDE models coming from financial problems have to be made ready so that a balance exists between stability properties and time.

To this end it may be useful to have a thorough study on schemes to be adopted for parallel or distributed processing which does not modify convergence and stability process.

2.4. Microstructure of financial markets (Loistl et al.)

The idea underlying this model has been proposed by Loistl (Loistl 1989): the market is made by the aggregation of many agents whose behaviour is driven by different goals and whose expectations are rather diversified (as opposite to the theory of uniform expectations). This means that the market price of a financial activity is not seen as an equilibrium price but as a match point between demand and offer of two single participants.

The proposed model is quite complex, involving the modelization of single agent's behaviour as well as new rules for aggregation of demand and offer among different segments of the markets. At the same time the model includes a high degree of parallelism because the agents work contemporarily but independently.

2.5. Connectionist modeling for time series analysis (Würtz and de Groot)

Neural nets are a very powerful tool for modeling problems related to different areas of applications and derive from a "biologically inspired model of the human brain" (Mills 1992).

A neural net is composed of nodes connected together in an organized topology so that from input nodes it produces output nodes using some kind of transformation and activation functions. The net is called a feedforward net when there are no feedback loops.

One of the main applications of feedforward nets is related to classification of a large amount of data and to representation or approximation of non linear functions. This latter characteristic has induced Würtz and al. (Würtz 1992) to use this tool, together with other statistical techniques, for non linear time series analysis in different application fields.

As far as is concerned finance, they get some interesting results in the problem of forecasting currency exchange rates. They found that the neural approach outperforms traditional methods even if the approach is in its preliminary stage and it lacks robustness.

Neural networks can also be viewed as a highly parallel computational process and this is very interesting because in a single tool we find the capacity for learning by examples and to be trained combined with the ability to manage large numbers of input data.

3. Expert systems and neural networks for the modeling of financial markets

3.1. The financial problem

Investment decisions in the stock market have to answer the trader's problem of "What and When" (to buy), namely the search for:

(a) sure and safe methods for estimating the state of the market and its trend;

(b) the right stock to buy and the time to buy it are chosen on the basis of two main approaches, known in literature as Fundamental Analysis and Technical Analysis.

Quite generally, it can be said that Fundamental analysis delivers an answer to the "what" question and Technical analysis can solve the "when" problem. In practice, other "environmental" factors should also be considered, besides those belonging to the areas of technical and fundamental theories. Such factors (e.g. economic, political and monetary aspects) may contribute to the formation of the analyst's opinion (Pring 1985).

The complexity of the problem outlined so far is such as to require a coordination which can only be provided by an expert able to analyze the huge amount of numerical data at hand. Their limited availability is the main reason why automatic solutions to the outlined problem can be sought for. In other words it is believed that the techniques adopted by the analysts are adequate and effective if the necessary correct information is available. However, such information is partially useless due to the inability to analyze it in real time.

3.2. An automatic solution to the problem

The potentialities of *Expert Systems* able to solve such problems are tempting: human expertise is rare, expensive, volatile and open to influence. Electronic experience, on the other hand, is affordable, easy to duplicate, uniform and continuously available. Furthermore, the coded knowledge, as the core of an expert system, can be seen as a sort of "institutional memory" of the strategies and techniques adopted (Waterman 1984). Therefore the design of an "optimal" expert system should be structured hierarchically in two levels, the lower of which includes the three specialized subsystems:

- Fundamental Analysis,
- Technical Analysis,
- Environmental Analysis,

coordinated by a higher-level supervising decision system carrying out a synthesis of the results of the different analyses. Since such an E.S. turns out to be too large a problem to manage, it will be suitable to identify a subproblem eligible for an E.S. solution.

Of the three analyses outlined above, the technical analysis appears as the most promising one. Indeed, technical analysis is more general and easier to design and implement. Furthermore new "technical" facts will arise more often than "fundamental" ones, requiring a frequent revision of the analysis. In other words: an expert system working with technical facts and technical expertise will be easier to implement and more useful than an expert system for the fundamental and environmental analysis.

An expert system solution to the problem is not only justified but also adequate. The actions required from the experts can be grouped and classified in three steps:

1. the acquisition and manipulation of numerical data concerning trading prices and volumes of shares;
2. the transformation of these numerical data into symbolic data;
3. the use of numerical and symbolic data of steps 1 and 2 to choose suitable trading strategies.

Operations in step 1. are normally carried out automatically through extensive use of conventional software for the algorithmic processing of numerical data. Several data bases to update market data are available. Routines to produce graphics information concerning prices and volumes, averages, moving averages, and all technical indicators computed from these are also available.

Operations in step 2. are usually carried out by experts with the partial support of automatic routines. The kind of operations which fall in this category are for example the drawing of trend lines, the identification of particular graphical patterns on the price plots (head and shoulder, triangle, ..), the breakout of trend lines and many others. Data obtained in this step are symbolic and naturally associated with some uncertainty.

The third step is usually carried out through the human expertise of the technical analyst to summarize several different concepts and deliver a decision. In order to reach a complete solution to the problem it is necessary:

- to represent and use symbolic data,
- to represent and use uncertain data,
- to build and search a deep and complex decision tree.

It is also essential that the solution of the problem meets the following requirements:

- the system must be able to justify its conclusion,
- the system behaviour should be changed or updated easily.

Because of these characteristics, the problem does not fit conventional software but, on the contrary, appears suitable for an expert system. In particular, the ability of the inference engine to build an already pruned decision tree allows to represent very large decision trees that otherwise could not be implemented (Lenat 1983).

3.3. A PROTOTYPE

In this framework, we have developed a prototyping system designed to solve problems belonging to steps 2. and 3. as outlined above. More precisely: the system is able to trace trend–lines, return–lines and to identify breakouts and simple patterns such as triangle formations on a price chart, (step 2). When a breakout is identified an expert system, fed by symbolic data produced in step 2, tries to foresee the behaviour of the market (step 3). The analysis carried out by the expert system is a semplified version of the trend–lines analysis integrated with rules of volume analysis.

Trendline analysis is the study of market behaviour through the drawing and analysis of the straight lines connecting some tops of the minor rallies (in a descending price market). A central role in this analysis is the identification of the relevant extrema in the price chart. This problem has been solved (Cavalli 1991) with the definition of *maximum* (minimum) *of size* k, in the following way:

Let p_j, $j = 1,..,n$ be a sequence of values of prices of a stock at day j. The value p_m is said to be a (local) maximum of size k of the sequence p_j, if the following relations hold:

[1] for all j, $m - k <= j < m$, $(p_j <= p_m \quad \text{or} \quad j < 1)$

[2] for all j, $m < j <= m + k$, $(p_j < \; p_m \quad \text{or} \quad j > n)$

[3] $(m + k - n) * (m - k - 1) >= 0$

[4] $p_{m-k-1} > p_m \quad \text{or} \quad p_{m+k+1} > p_m$.

The definition of local minimum can be obtained reversing in [1] and [2] the inequalities between p_m and p_j. A local maximum or a local minimum is called a peak.

Relations [1] and [2] allow to extend the values p_j to the left of p_1 [1] and to the right of p_n [2], with arbitrary values, relation [3] avoids extending the values on both sides, and [4] forces a peak to be as wide as possible.

In a "flat" peak, the value of m is forced, by [1], to the right end of the flat area. (This is in accordance with the empirical rule adopted by the analyst to draw trend lines). The above definitions introduce a classifying criterion among peaks and, using a suitable value for k, can filter minor fluctuations in the price chart.

We have implemented a method of detecting peaks of different size and an extensive testing on time series of stock prices has been done. Different methods for drawing trend lines have been tried and tested. All these methods are based on the definition of extrema given in [1]–[4] above, supported by an extensive empirical knowledge provided by suitable program routines. The system, in its current implementation, has the following capabilities:

1) To identify significant peaks. In this prospect, the value $k = 10$ (size) appears to provide the best experimental results.
2) To draw straight lines joining maximum (minimum) peaks.
3) On the basis of the results in 1) and 2), to identify the trend(s) and to draw the trend– and return–lines.
4) To recognize the occurrence of particular cases such as trendline breakout or a triangle–shaped formation.

The expert system, which has been developed using SNARK (Lauriere 1985), has been tested with a set of 120 breakout situations selected by the experts. The breakout cases in the test set reflect different situations observed in the italian stock market, in the period 1983 — 1991, with respect to the following shares: Burgo, Cogefar, Alitalia and the Comit index. In this phase the system ran correctly in 70% of the test cases.

3.4. THE NEURAL NETWORK APPROACH

On the grounds of such encouraging preliminary results, we foresee an improvement of this approach in two main lines of work.

First of all, we see a possible and suitable application of a neural network in step 2. The implemented software is in fact able to recognize only some simple patterns, like triangles and channels, while other configurations, like head and shoulder, are impossible to detect with this approach. Such a kind of configurations can typically be processed by a neural network trained through a set of chosen and well–posed examples. Thus we are working in the direction of restructuring step 2 adding to the previous system (or replacing the previous system with) a neural network subsystem able to complete the identification process of step 2. In this way we expect an increased robustness in the whole pattern recognition process as well as a better efficiency in terms of response time of the method.

Step 3. is implemented through an expert system which is characterized, at professional level, by a large number of rules extracted from interviews with experts. Unfortunately this knowledge acquisition, which must be frequently updated due to various changing conditions, is a time comsuming and expensive task. In our opinion, the semi automatic knowledge acquisition capability of neural networks can also be exploited. Due to the learning by examples ability of neural networks, the system update process can be done more easily because of the reduced effort required of the experts who must devise a suitable training set of data. Nevertheless neural learning suffers from the disadvantage to be unable to explain the chain of reasoning followed to reach a specific solution. For this reason we think of two possible alternatives to overcome this severe limitation:

a) a justifier expert system coupled with a solver neural network;

b) the development of explanation facilities in terms of relations given by formal rules describing the input nodes and output nodes (Pau 1989).

4. Conclusions

Some relevant applications, which make use of information technology to devise intelligent solutions encapsulating different kinds of heuristics, have been presented.

We have addressed the same issue in the particular area of technical analysis where we made extensive use of heuristic knowledge in different ways. Heuristic knowledge is spread over the program routines designed to detect peaks and to draw trend–lines; and it is also present in the expert system which tries to foresee the behaviour of the price trend after a breakout.

Also the potential solution based on neural network technology can be classified as an heuristic one.

Our results confirm that knowledge–based techniques combined with heuristics are less critical than some solely quantitative techniques simply because they can justify how "smart" they are.

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