AN INNOVATIVE DECISION SUPPORT SYSTEM FOR STRATEGIC INVESTMENTS IN POWER SECTOR

GABRIELA PRELIPCEAN
MIRCEA BOSCOIANU
Faculty of Economics and Public Administration
University "Stefan cel Mare" of Suceava
13 Universitatii Street, 720229 – Suceava
ROMANIA
gprelipcean@yahoo.com, mircea_boscoianu@yahoo.com

Abstract: Energy infrastructure investments occur in a highly dynamic context, with many different risks. In project investment evaluation, governments, investors and financial intermediaries are interested in a methodology that include the risks and uncertainties in power sector (due to changing energy price in competitive energy markets, uncertain future carbon price, uncertain government policy on climate change, and uncertain international regime on climate change mechanism). The risk of political shocks associated with high uncertainties and volatility in the aftermath of global markets turbulences could dramatically change the investment conditions and technology selection in strategic energy sector. The analysis of the impact of these policies on power investment is based on Real Options Analysis (ROA) inspired from Dixit, Pindyck (1994) optimization and Yang, Blyth (2006) model combined with neural networks (NN).

Keywords: Discounted cash flow (DCF), Real option analysis (ROA), Neural networks (NN), Price uncertainty, Volatility, Flexibility.

1 Introduction

Financing the investments in energy critical infrastructure represents a very important task in the current situation of the recent turbulences in the financial global markets. The total investment requirements of the global energy over next 20 years are estimated to 14 trillion Euros. The bulk of that investment is needed for electricity markets, although we could place the requirement for oil and gas projects as being of a similar magnitude. The required rate of investment flows is bigger than the capital available to achieve optimal strategic solutions. The energy market radically differs from other markets because of the highly complexity of the market rules, the production process and the delivery of the electricity, the different patterns of the restructuring of the electricity industry. The new energy market is not a perfect market. Not all of participants, both public and private companies and institutions respond in an efficient manner to market signals. There are high asymmetries in the access to capital and other market imperfections that prolonged the chronic underinvestment in energy sector.

The success of competitive Romanian energy market and the capability to assure energy security is linked to the internal market's ability to finance the investments necessary in the critical infrastructure.

Based on the New Energy Security Strategy, investments in energy sector faces some major challenges: reforms of energy markets, competition and market functionality, requirements related to climate change policies, the rising of energy resources prices, the actual global financial turbulences. *The main characteristics of investments* in energy sector are: investment *irreversibility*; the *high uncertainty* on future ROI; the *flexible timing* investment. In the picture of these conflicting dynamics, power sector investors should adopt new methods to complement the traditional approach of deterministic DCF.

Such assessments which guide government's policy formulations to sustain and secure domestic power markets are made by using new models to address the complex and myriad variables influencing investment in power generation.

Strategic timing of investment and choice of technology are of principal interest to policy-makers. ROA could become a useful tool for the government policy makers and private investors to quantitatively analyze the impacts of policy shocks, energy price uncertainty and the global financial crisis on investments in energy.

Decision making in a volatile, dynamically changing environment is very complex and requires innovative decision support systems (IDSS) based on mixed techniques of soft computing. A new

approach based on evolving agents in a dynamic environment is introduced .
IDSS should solve the problems with huge amount of information distributed among a high number of variables. The aim is to offer innovative explanation facilities, based on flexible decision rules, dealing with large databases with a lot of redundant information, or coping with the lack of data. Strategic decision making process involves multiple levels of processing, comparing different possible solutions, using alternatives, sometimes in a recurrent way.
The soft computing techniques (neural networks, NN, fuzzy logic FL, genetic algorithms), and other tools like advanced statistical methods, hybrid systems, are combined with financial analysis methods.

2. The recent literature regarding ROA and NN applications

The interest is to select alternative investment opportunities that result in high volatility and uncertainty, in an optimal manner. The investors' preferences in energy markets and the optimality of a portfolio, is similar to finance modeling.
Friedman, Savage (1948) proposed *utility functions* and their connection with the implied risk preferences. Investors could be: *risk-averse, risk-neutral,* or *risk-seeking.* The risk preferences translate to the properties of utility functions: risk-averse investor's utility function is strictly concave, while the risk-neutral investor's is linear and the risk-seeking investor's strictly convex. *Markowitz (1952)* optimal portfolio selection method is focused on the choice between several risky assets and depends on the estimates for returns and covariance. Such selection results in an estimated variance minimizing portfolio that has an estimated expected return. *Tobin* (1958) included the possibility of holding capital in a risk-free asset, introducing new investment risk-return considerations.
After Markowitz and Tobin, the literature has combined optimal portfolio selection and utility function theories. Hanoch, Levy (1969) generalized mean-variance setting to any utility function. Pratt (1964) and Arrow (1965) proposed utility functions in terms of how large a risk premium a risk-averse investor with some specific utility function would like to receive in comparison to a risk-neutral investor. Kallberg, Ziemba (1983) studied the properties of utility functions in optimal portfolio selection problems, concluding that the selection of a utility function to match certain risk preferences can be build on the basis of Arrow-Pratt risk characterization. Luenberger (1993) considered theoretical justifications for choosing a particular utility function that maximizes the expected growth, while Hakansson, Ziemba (1997) considered the importance of utility function choice for the long-term growth in wealth. Rabin (2000) and Rabin, Thaler (2003) criticized the utility theory and the assumption that rational investors are risk-averse and demonstrated that the estimation of a concave utility function based on a decision on a certain level of wealth implies irrational choices on other levels of wealth. Rabin, Thaler suggested an alternative functional form that would capture risk preferences in a more relevant manner.
New optimal portfolio selection literature is based on utility maximization over time. The static one-period optimal portfolio selection theory was elaborated to a dynamic multi-period setting by Samuelson (1969) in discrete time and by Merton (1969, 1971) in continuous time. Dynamic optimal portfolio selection framework allows portfolio adjustments. If the investment period is long, the possibility of adjusting the portfolio according to new information yields better optimization results. *Steinbach* (2003) presented some new refinements in the modern optimal portfolio selection theory.
The participants in uncertain markets often have an interest in *hedging against risks*. Leland (1998) argued that hedging enables greater leverage, meaning the company can better optimize its capital structure. The question of *hedging can be formulated as an optimal portfolio selection problem*.
The introduction of electricity spot and derivatives created new opportunities. High spot market price volatility exposes spot market participants to a high level of profit uncertainty. Hedging with spot electricity derivatives reduces profit uncertainty. The problem is to know *how much to hedge and with what instruments*. Kaye et al. (1990) and Amundsen and Singh (1992) proposed the use of derivatives to hedge risks in spot electricity markets. Weron (2000) presented a detailed analysis based on the special characteristics of electricity markets. Bessembinder, Lemmon (2002) argued that companies operating in electricity markets could benefit from reducing their profit uncertainty more than companies in other sectors.
Bjorgan (2001) presented an application of the Markowitz model together with hedging decisions. Fleten (1999, 2004) and Mo (2003) analyzed a stochastic programming approach for solving the *optimal portfolio selection problem in electricity markets* (optimal generation decisions and hedging decisions are coordinated). Bjorkvoll (2001) optimized generation and the corresponding hedging portfolio but separated the generation and hedging decisions demonstrating that hedging decisions that take place with market

prices do not affect the generation decisions.

In addition to the influence of risk on optimal portfolio selection, the quantification of risk is an interesting question in itself. Markowitz (1952) associated risk with the variation of portfolio return but increased competition and consequent tighter margins have increased the need to a stronger risk analysis. Baumol (1963) presented an alternative risk measure, the *value-at-risk (VaR)* measure. Jorion (1997) presented a thorough analysis on VaR defined for the wealth in a portfolio π at a given probability α and over a given time τ. But VaR does not indicate how low wealth can be if the probabilistic limit breaks. Artzner (2001) introduced risk measures that are more suitable for optimization problems and give more intuitive risk quantifications. Follmer and Schied (2002) gave a detailed analysis of the properties of risk measures. The choice of a risk measure is dependent on investors' preferences, as is the choice of a utility function.

Philipovich (1997) applied value-at-risk to electricity markets. In finance, value-at-risk measures the potential change in portfolio wealth in the short-term. Electricity portfolios that include physical assets are held over a longer time. Lemming (2004) presented a variation of value-at-risk called the *profit-at-risk* that gives more relevant risk quantifications in electricity markets. Profit-and-risk is identical in form to value-at-risk, but the time horizon is different. Value-at-risk focuses on the short-term changes in portfolio wealth, while profit-at-risk focuses on the wealth after longer time periods.

ROA was proposed by *Myers (1977)*, who first identified investments in real assets as mere options. Laughton (2003) applied ROA to the assessment of GHG sequestration. Using ROA in an environment of uncertain CO_2 price, Sekar (2005) analyzed investments in different technologies by using a mix between market-based valuation for cash flow uncertainty with Monte-Carlo simulation and dynamic modeling of uncertainty. Rothwell (2006) proposed a risk analysis of new nuclear power plants based on modeling three uncertainties: price risk, output risk and cost risk. Other recent *applications of ROA in energy sector* include: Siddiqui (2007), which evaluated the strategy for renewable energy research, development, demonstration, and development in US; Marreco, Carpio (2006), which examined the flexibility of the Brazilian power system; Kuper, Soest (2006), which evaluated the influence of uncertain oil prices on energy use.

Persaud proposed *a model for risk analysis on crashes of currencies* which considers a *crash situation* when the currency has been devaluated more than 15%. The parameters used to evaluate the likelihood of a crash are: a measure of currency overvaluation, an expected domestic output growth, the ratio of reserves versus external debt, a composite measure of international financial contagion.

The methods in the literature require a reliable knowledge on the underlying rules of the financial and economic systems and can not be easily adjusted to a new economic or financial situation, but are applicable only when crises occur according to recurrent and known patterns.

FL systems functioning is based on human expert rules but are not flexible enough to react to changes in the reality. Changing the rules usually is difficult, and nobody can articulate the perfect set of rules that do not have to change in a future time.

Hawley, Johnson, Raina (1990)-identified various potential uses of neural networks (NN) in financial market applications (simulation, prediction, evaluation).

In the *literature on NN* for *financial IDSS* are used, mainly multi-layer perceptrons (MLP), radial basis functions (RBF), and self-organising feature maps (SOM). NN are suitable for nonlinear problems and have been utilized with success *in financial market prediction* but also in determining the *optimal buy/ sell timing* and recognizing a *specific price pattern* (Kamijo, Tanigawa, 1990). *NN* models are efficient, but they do not allow easily for dynamic on-line training, for changing the parameters in an on-line mode, for combining data and knowledge (rules) into one system.

MLP and RBF model and a RBF model on option pricing (Hutchinson, 2000) proved to outperform several other models, that include a direct application of Black-Scholes formula, ordinary least squares, and projection pursuit. In Deboeck is presented a substantial study of applying SOM to financial markets is presented. Some authors proposed special models for emerging and new markets are mapped into a SOM that shows groups/ clusters of similar economies.

GA models are based on generating possible solutions to a problem and evaluating their performance based on a fitness function specified in advance. Software based on GA simulation can works directly on data in an Excel format. The main advantage of GAs is that they do not require much knowledge on the underlying rules, but a fitness function to evaluate how good solutions are. The main disadvantages of GA are: low computational speed; they do not necessarily provide with the best solution as they are heuristically based; they do not work in on-line and real time modes.

The use of Dynamic System Analysis (DSA) in markets is based on the assumption that a complex dynamic system can be situated in one of four states projected in a two-dimensional space of group thinking-fundamental bias: random walk, chaotic market, coherent bull market, coherent bear market. Some authors considered an index prediction problem as equivalent to the prediction of a chaotic process with different characteristics at different time scales and a high frequency index prediction (daily/ session prediction) being attempted after the low frequency one (monthly/ annual prediction) is performed.

Hybrid systems combine the methods presented above into one system either in a *loose way* (different modules in the same system use different methods), or in a *tight way* (the methods are mixed at a low level). The main advantage is that the methods deal with both data and expert rules, using both statistical formulas and heuristics/ hints

The major problems of these approaches:

-not consider *the complexity of the global problem* with *hierarchical levels* for decision making that include applying low-level processing and higher level expert knowledge;

-not consider *uncertainties at different levels of information processing* and combining them or propagating them in a task dependent way to the final
decision making block;

-not apply sufficient variety of techniques and choose the most appropriate for each sub-task;

-not offer *adjustment of variable sets, optimization criteria, rules, even if the real situation changes over time.*

3. An integrated framework for modeling strategic investment decisions

The rate of capital mobilization is more important than *capital availability* and depends on market signals, particularly on the efficiency of longer term prices. Even if in general the market is sending the correct price signals, there can still be inequalities and imbalances in the access to capital. Industries can be constrained in the scope of their sources of capital. They can for instance find they have less than optimal access to international capital and be confined to domestic capital markets with insufficient liquidity. International and national sanctions can impinge on access to capital. Differential credit ratings due to past sector, national or regional performance can also impact to capital access. This leads to our second proposition;

The *access to capital* can be uneven in small or emerging markets, and this task is more complicated in periods of high turbulences, like the one in the aftermath of subprime crisis.

The uncertainties in the amount of long term capital are due to supply side uncertainties and most particularly the rate of depreciation influence the optimal investments in energy. Some of the investments being made today will need total replacement within 20-25 years, and all of the existing fixed capital will need significant replacement. The bulk of investment in energy over this period will replace existing supply side capacity, rather than to service incremental demand. It is important to note that the current problems in energy infrastructure are related to governments promoting and policy.

A new perception of governments and markets towards the imperatives of energy investment represents an important part of reversing the chronic process of underinvestment. The problem of underinvestment in energy is critical in the context of global contagious dual crises in the aftermath of *subprime* crisis and in the context of high volatility and uncertainty of primary non regenerable resources prices. Given the lags involved, an approach that is too complacent or dogmatic may have consequences that are difficult to reverse. In general, the policy of least regret is normally the optimal one in terms of energy investment and it's financing.

Current EU energy security policy is closely related to Common Foreign and Security Policy (CFSP) and contains a link between energy and climate change policy, external relations, indigenous energy supply and the internal energy market efforts. There are some disagreements regarding the protection of national energy industries (Germany, France, and Spain) and a reluctance to open energy sectors to more competition.

EU is increasing its role in coordinating and financing the development of RES and the storage and use of emergent energy supply. EU also plays a larger role in determining power grid interconnection arrangements and energy infrastructure investment levels.

The EU-27 will need to invest approximately 1.1 trillion Euros in new technologies over the next 14 years in order to achieve their carbon emissions and accompanying renewable and energy efficiency targets (McKinsey and Company Report, 2007). This is a long term effort, made in difficult financial market conditions and the strategy to overcome the actual liquidity crisis represents a difficult milestone for the future.

The framework should include a module for *forecasting uncertainties* capable *to treat circumstances under which it is optimal to exercise the options* for each moment during the investment life cycle.

Database which includes energy prices, carbon prices, technologies of power production, other market prices and correlations, is processed in the light of different scenarios. The search process for breakeven points where power production may switch between generation technologies is based on DCF analysis. The high volatility (energy, carbon prices) which drive the dynamics of critical points of technology switching, the correlations between markets and other data are engineered in a model which combined ROA with soft computing techniques.

a) The integrated database includes different groups of data and information: economic and financial (capital investment costs, operation and maintenance costs, fuel prices and CO_2 emissions trading prices), technical, environmental and related financial markets.

Huge amount of data is being collected that includes different level of information: macroeconomic information (EUROSTAT, the European Central Bank Monthly Bulletin, OECS, IMF, Datastream); financial data and markets (DataStream, Bloomberg, Reuter). Different time-scales of data are present in the data repository.

It is very difficult to deal with this relevant amount of data without preparing at least a general initial structure; in this way we have built two main prospects: the 3D sources dictionary and the data dictionary.

The first prospect has in the x-axis the countries relevant for power and energy risk analysis; the participants, the potential entrants, the big players vs. emerging countries to proxy for any contagion effect; in the y-axis we have set all the types of data which could be useful for the future research project. The third dimension is concerned with the source of the gathered information; every single variable related to every involved country has been collected by a specific source. This aspect is important to evaluate mainly the reliability of the data, but also the degree of homogeneity in the data set. In fact, choosing the data source which covers the most part of the involved countries allows to achieve high degree of similarity in the modeling procedure and in the updating timing and method. Considering the specific purpose of the analysis, we rely upon official statistics from Eurostat for most of the required data.

The second prospect, named "data dictionary", is formed as a table with columns reporting the specific features of each data series; the most important ones are the first available date, the frequency of collection, and the mnemonic code, which is an alphanumeric expression useful to automate the information downloading process. We have distinguished two broad categories of data that are being collected. The first level of information is concerned with macroeconomic variables; the second level is more specific and regards financial market data. A third level of information, connected with qualitative knowledge, for example the political situation or particular news, is not formally considered in this first model implementation. The typical feature of the first group of variables - macroeconomic data - is the low frequency of collection, which is monthly, quarterly or even yearly, depending on the specific sector; another important feature is the potential variety of sources for the same kind of data. A third property is the potential different calculus and updating procedure for the same sort of indices. The most relevant macroeconomic data are generally available either as historical time series, or as a consensus forecast.

The financial market variables are collected more frequently, even on a daily basis, and are usually released officially by the exchanges. In our research project we have tried to consider not only the past evolution of the various financial series, but also the market expectations implied in option prices; there is a growing literature dealing with this aspect with two main approaches. The simpler approach is related to the calculation of implied volatility at different monetary degrees as a forecast for expected volatility. In the second approach the underlying risk neutral density function is extracted from option market prices; it is very useful subsequently to monitor the evolution of the various moment of the probability distribution.

b) *The uncertainty modeling* is based on geometric Brownian motion random walk model and neural networks techniques and includes: modeling price uncertainties, modeling price shocks, modeling price correlations. The interest is to simulate uncertain prices and the effects of different policies on price shocks

c) *Investment analysis in different steps*. Based on the evaluation of deterministic NPVs for different technologies, DCF does not include the investment flexibility and the stochastic price changing.

$$NPV = \sum_{t=1}^{T} \frac{C(P_c)_t}{(1+r)^t} - C_0 \qquad (1)$$

where: C_0 – the unit construction costs; P_c – the carbon price; $C(P_c)_t$ – the cash in-flow of the projects.

Dynamic stochastic analysis use Monte Carlo simulation to incorporate the estimations of uncertainties into the model variables. The stochastic approach permits the analysis of *the value of operational flexibility* which offers the capability to leverage favorable/ adverse price conditions.

Input data such as primary randomized energy prices, electricity prices, carbon trading prices, related markets, are presented by using a statistical distribution and the model calculates global stochastic.

$$\mathrm{NPV} = \sum_{t=1}^{T} \frac{C(\mathrm{Stochastic}\ P_c \ \&\ P_e)_t}{(1+r)^t} - C_0 \qquad (2)$$

where: P_c and P_e – the carbon price and energy price; C(Stochastic P_c&P_e)$_t$ – the cash in-flow.

In *Dixit, Pindyck (1994)* ROA optimization includes a procedure of searching the optimal moment to invest and the evaluation of the investment risk premiums from the top to the bottom of the proposed decision tree. At each moment *t,* the model compare the NPV of the project taking into account real shocks and energy price volatilities under different scenarios (invest now/ hold on the investment until next period). By comparing the NPVs at all the time periods under these scenarios, it results the optimal investment timing.

The use of ROA takes the advantage of including two critical elements: *scenarios* and *options*. An *option* always has a *source scenario* (an existing project which is generating cash flow without additional capital investment, or a green field investment) and at least one *target scenario* (the existing power plant with improved energy efficiency or a new technology). An *option* defines the *opportunity of switching irreversibly from one scenario to another*. The action of switching scenarios is known as exercising the option (investing in the project) which entails a cost. The *flexibility* of ROA includes several *strategic forms*:

- the ability to invest now and make follow-up investments later if the original project is a success (a *growth* option)
- the ability to abandon the project if it is unsuccessful (*exit* option)
- the ability to vary inputs, output or production methods in response to changes in prices or demand *(a flexibility* option).
- the *ability to wait and learn*; resolving uncertainty before investing (*timing* option).

4. The use of ROA in flexible strategic investments under high uncertainty and volatility

A *real option* is a permission (with different value in time) to undertake investment decisions, typically an option to make a capital investment. ROA offers a nuanced approach to strategic investment that considers the value of the opened options for budget decision-makers and cope with investment uncertainty and flexibility. ROA sees *the investment problem and uncertainty in a particular way* focused on the *timing of the decision* not on whether to do the project or not. It has a strong ability to explicitly analyze the effects of different sources of uncertainty on the cash-flow, providing a powerful tool for giving insights into the question that motivated climate change policy study.

Actual investment behavior could deviate significantly from traditional expectations, which could have very important implications for policy makers:

- ROA may indicate that the price differential of carbon required triggering investments in low-emitting technologies (the uncertainty surrounding the carbon price is created by government policies);
- ROA helps explain why actual investment rates tend to differ from expectations, and why policies designed to stimulate investment may be less effective than expected;
- Uncertainty will affect different technologies to different extents, and so the presence of uncertainty may lead to unexpected trends in technology uptake.

The uncertainties relating to climate change policy could be expressed through the carbon price, fuel and electricity price uncertainty, with different types of variations:

-short-term volatility (rapid price variation) does not significantly alter the investment decision

- in long-term uncertainty (relating to weather, technology costs, and other market conditions) price variations are considered with a random walk (geometric Brownian motion) price process in which expectations of future prices may drift up/ down but on average would remain unchanged.
- climate policy uncertainty is represented by a discreet jump in price in the future (price shock).

Yang, Blyth (2006) proposed a cash-flow model which uses randomized price paths for the main elements of the cash flow (electricity price, and gas, coal, CO_2 prices) and includes the technical duration of the plant.

The model uses a Monte Carlo method to build up a probability distribution for the gross margin (the final cash flow, measured as after-tax gross margin). Cash-flow is calculated many times, using a different price path, in order to build up a distribution of gross margin outcomes.

The *option to invest* is incorporated by allowing the model to make an irreversible switch between different cash-flow streams in any given year. The selection between the existing cash-flow, and *a new invest option cash flow* which represents the expected gross margin of the technology being considered is made on the basis of whether the expected pay-off from making the investment is better than the expected pay-off from sticking with the existing cash-flow. The novelty is that the valuation of the *do nothing option* includes the possibility that the investment will be made at a

later date. The model is able to *optimize the timing of investment* by building up an investment rule that takes account of expected future events (price shocks, policy interventions), and comparing current conditions against this investment rule.
The *investment rule* is established by running the simulation of prices backwards, starting from the end-date and working back towards year 1, and in each year comparing the expected value of the "do nothing" and "invest" options, where the "do nothing" option takes account of optimized values in future years that have been calculated in previous steps (a dynamic programming approach). It is assumed that *perfect quality information* is delivered immediately after the jump. In reality, it is a gradually process.
Instead to look at the cost-effectiveness of different investments, the focus is *to understand the difference that uncertainty can make to an investment decision* (the extent to which it raises the investment threshold). It results a clear distinction between DCF factors that affect the profitability of a project and factors that affect the *additional investment threshold caused by uncertainty*. After choosing the conditions of fuel/ carbon price such that the investment appears financially viable under DCF rule, it is analyzed the effect of introducing *uncertainty*. The interest is to establish what the new investment criteria are under conditions of uncertainty (what is the new threshold in terms of project profitability required in order for the decision-maker to continue the investment.
Under uncertainty, the gross margin would need to exceed some threshold (as a percentage of capital cost) over and above the capital cost in order to trigger immediate investment (to overcome the value of the option to wait).

5 The Adaptive IDSS Module

5.1 Basic aspects of hybrid systems

Hybrid systems combine different techniques of computational intelligence with traditional statistical methods. Hybrid systems are especially suitable for building IDSS. Market index predictions requires a hybrid system. Several modules are included in the IDSS: normalisation, moving averages calculation; predicting the next value for the index and longer-term values; strategic decision making that takes into account rules on the political and economic situation; extracting trading rules from the system (Fig. 1). The NN is used to predict the next value of the index based on the current and the previous-day values. The use of NN offers the ability to detect and assimilate relationships between these variables with good potential in different market forecasting. There are many ways and combinations in which NN can be specified and many types of data can be simultaneously used.
The predicted value from the NN module is mixed with *expert rules* on the current political and economic global situation in a FL module. Another module is devoted to extracting fuzzy trading rules, which are used to explain the current behaviour of the markets.
The FuzzyCOPE/1 decision making environment is based on a different modules: data processing (normalisation, fuzzification, filtering); multilayer perceptron(MLP); self-organising map (SOM); Kasabov fuzzy neural network (KFNN); FL Zadeh inference engine (FLZIE); production rule-based system CLIPS and FuzzyCLIPS. The Fuzzy-COPE/1 environment has been extended to FuzzyCOPE/3 with the inclusion of new MLP and SOM learning modes, and new modes for learning, rule extraction and rule insertion in KFNN.
The hybrid system environments and the hybrid systems built with them, have been very useful techniques, but the complexity and the dynamics and the volatility of the real markets in energy more sophisticated methods, capable to change as they operate, capable to update their knowledge and to refine the model through interaction with the environment.

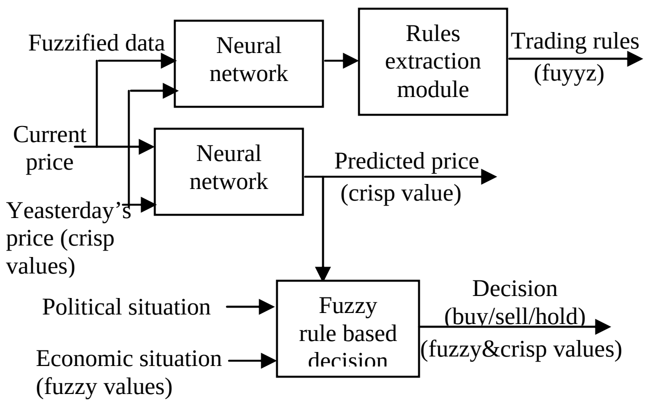
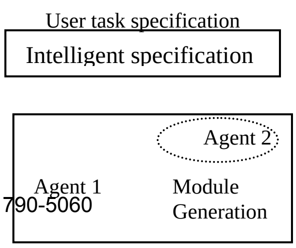


Fig. 1. The architecture of a hybrid decision system for aggressive trading

ECOS is another framework for learning and evolving algorithms, rule extraction and rule insertion algorithms based on an evolving FNN capable to learn in an incremental, adaptive way through one-pass propagation of any new data. EFNN is faster than FNN/ MLP and can learn data in an on-line mode. EFNN do not have a fixed structure, but it starts evolving/learning with no rule (hidden) nodes and grow as data is presented. The main advantages of EFNN are:
-they *can learn in an on-line mode any new data available*;
-they can work in a *complex environment with changing dynamics* (a system in random walk state,

moves to a chaotic state, and then to quasi periodic state, is predicted by learning all the time the new behaviour without human intervention for parameter adjustment;
-they can be used to mix expert rules and data as there are algorithms for rule insertion and rule extraction;
-they can cluster data in an on-line mode without pre-defining the number of clusters, or the dimensionality / size of the problem space;
-they can be used in supervised/ unsupervised learning modes to predict future values of the output variables.
The Adaptive Intelligent Expert Systems (AIES), is a new expert system based on dynamic generation of interconnected modules (agents). This is in sharp contrast with the conventional expert systems and IDSS that usually have a fixed structure of modules and a fixed rule base. Although traditional expert systems and classic DSS have been successful, there was only a very little flexibility left for the expert system to adapt to changes required by the user, or by the dynamically changing environment in which the expert system and the DSS respectively operated.

AIES consist of a series of modules which are agent-based and are generated in a flexible manner. In Fig. 2 is presented the general architecture of AIES. The user specifies the initial problem parameters and tasks to be solved. The AIES then creates Modules that may initially have no rules or may be set up with rules from the Expert Knowledge Base. The Modules combine the rules with the data from the Environment. Modules are continuously trained with data from the Environment. Rules may be extracted from trained FNN/ EFNN for later analysis, or for the creation of new Modules. The Modules dynamically adapt their rule sets as the environment changes since the number of rules is dependent on the data presented to the Modules. Modules (agents) are dynamically created, updated and connected in an on-line mode. They can be removed if they are no more needed at a later stage of the operation of the AIES.



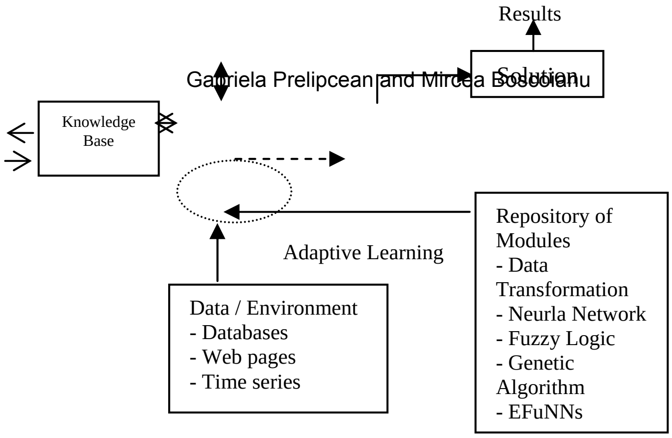


Fig. 2. A block diagram of an agent-based, adaptive intelligent decision support system HIDSS that uses the architecture of an AIES

5.2. The module for risk analysis in power sector investments

The aim is to develop a computational model for analyzing and critical *anticipating signals of abrupt changes of volatility in markets*. The system will be aimed at assessing the possibility of speculative attacks against specific markets.
The conceptual model underlying the computational model will be derived from a representation of markets as complex dynamic systems, whose stochastic behavior is influenced by *exogenous shocks* and *endogenous uncertainty*, the latter caused by interaction among market participants (degree of consensus, crowd behavior parameter). The system will be fed with information from different sources:
- macroeconomic and macro-financial indicators like real exchange rates, inflation differentials, Government deficit, aggregate liquidity and solvency measures (debt/asset ratio, reserve/debt ratio);
- risk spread on debt securities issued by sovereign and private borrowers;
- risks in non-renewable resources markets; the aggressive speculations;
- risk appetite of investors in financial markets;
- returns and historical volatility in markets (spot, derivatives);
- signals of trend, reversal and change of regime from technical analysis of real/ financial prices (moving averages, resistance and support levels, relative strength indicators); these signals will serve as proxy variables for endogenous uncertainty;
- implied volatility in derivatives and expected distributions extracted;
- recent episodes of instability/ fragility in the context of contagion.

The logic of the system will be designed as an extension of existing event risk models applied to foreign exchange markets. The system will be tested on a set of recent episodes of market crash, and then extended taking care of unique features of the new EMU monetary regime. The system will produce a rich informative output, consisting of descriptive reports and warning signals.

Firstly, the system will provide an intelligent interface to information currently analyzed by economists and traders. Users will be able to navigate through a rich set of economic and financial data presented in tables and graphs. The presentation will focus on phenomena pertaining to the economic performance in emerging markets, emphasizing divergences at the EU level.

Secondly, the system will provide signals and indicators reflecting the likelihood of a crash in EU financial markets. An extensive set of symptoms of financial fragility will be monitored in credit, bond and stock markets. New events will be checked against typical patterns of evolution of financial crises.

The system will provide a valuable support to analysts and decision makers in two ways: (1) selecting relevant information to be subsequently analyzed by human experts and (2) extracting and synthesizing signals from a vast array of information sources.

5.3 A modular multilevel IDSS solution

The main sub- modules are:

a) *Feature selection*. It performs filtering of the input information, feature extraction and forming input vectors. Typical features extracted from the input data either in an on-line mode or from the already stored data in files are: basic statistical parameters; probability distribution and cluster information; moving averages; wavelet transformations; power spectrum/ FFT frequency characteristics; main frequencies; Lyapunov coefficients; fractal dimensions; derivatives; skewness measures. The transformations are performed in the pre-processing modules (feature extraction) of the system applied to certain information input streams.

b) *Learning and memory*. Is a multi-modular, evolving structure of NN frame where the information/ patterns are stored. It can be built with the use of MLP, SOM, ESOM, FNN, EFNN. There are several levels of processing in these modules *in terms of timing*: daily updated modules (for daily financial prediction and daily input data), weekly/ monthly/ yearly updated modules, longer term predicted results.

This structure will include also several modules to deal with different levels and scales of prediction dealing with: predicting values/ differences; predicting short/ long term trends.

c) *Top-level decision* consists of several modules, each taking decision on a particular problem. The modules receive input from the NN, inputs from other variables in the data, qualitative input from users, and make decisions on possible critical situations that might occur.

These modules can send a feedback to the NN and the feature extraction part of the system in terms of requiring more information, different scenarios to be explored, different features extracted. These modules are mainly rule based with the use of production systems, flat FL rules, FNN/ EFNN that can represent both fuzzy rules and data. There are several groups that interact between each other, for example:

-the group of modules that deal with *global risk evaluation problems*

-the group for important economic factors and their results can be used either separately, or by the modules of type above:

d) *Auction modules*, that take the output from the higher-level decision modules and produce output results or send output (control) information in an on-line or in an off-line mode to institutions that should be alerted on a critical situation.

e) *Self-analysis and rule extraction modules*. This part extracts compressed abstract information from the NN and from the decision modules in different forms of rules, abstract associations. Initially the IDSS will have a predefined structure of modules and very few connections between them defined through prior knowledge. Gradually, the system will become more and more organized.

Each of the modules in the system are built, or automatically generated from the agent modules: data processing modules (normalisation, moving averages, FFT, filtering, wavelet transformation, fractal analysis, chaos analysis); production rules in JESS; fuzzy inference rules, MLP, SOM, ESOM, FNN, EFNN, Hidden-Markov Models

6. Conclusions

An integrated framework for analyzing the effects of *energy resources, carbon and related markets prices, financial turbulences on global project risk and investment strategy* was presented. The novelty is to incorporate ROA and NN methodologies, capable to quantify the influence of different policy shocks, the high volatility and uncertainty of prices evolution in energy sector.

ROA enables modeling of individual risk factors, thus informing a comparison of the relative influence of prices uncertainties. It permits a comparative analysis of the effects of different policy designs, the impact of climate change policy shocks uncertainty with critical influence on market uncertainty regarding power investment.

The IDSS architecture for different levels of analysis and decision making is presented. It takes into account the relevant changes in the global energy markets and the world financial markets, that includes: the European Union level; the global world economies level; national level; company and bank level.

References:

[1] Aiken, M. and M. Bsat. (1999) "Forecasting Market Trends with Neural Networks." Information Systems Management 16 (4), 42-48.

[2] Amilon, H. (2001) "A Neural Network versus Black-Scholes: A Comparison of Pricing and Hedging Performances" Department of Economics, Lund University, Lund, Sweden.

[3] Chen, S.-H. and W.-C. Lee. (1997) "Option Pricing with Genetic Algorithms: A Second Report." IEEE, 21-25.

[4] CPB Memorandum (2003), "Emission Trading and the European Electricity Market"

[5] Datz, J. O. and D. L. McCormick. (2000). *The Encyclopedia of Trading Strategies,* New York: McGraw-Hill.

[6] Dixit & Pindyck (1994), "Investment under Uncertainty", Princeton University Press.

[7] ECN (2005), "CO_2 price dynamics: The implications of EU emissions trading for the price of electricity", ECN-C--05-081, The Netherlands.

[8] Hamilton, K. (2005), 'The Finance-Policy Gap: Policy Conditions for Attracting Long-Term Investment', in Tang, K, ed. 2005. The Finance of Climate Change, London: Risk Books.

[9] Kassicieh, S. K., T. L. Paez and G. Vora. (1997) "Investment Decisions Using Genetic Algorithms - Proceedings of the Thirtieth Hawaii International Conference on System Sciences 5, 484-490, 7-10 January

[11] Kuo, R. J., L. C. Lee and C. F. Lee. (1996) "Integration of Artificial Neural Networks and Fuzzy Delphi for Stock Market Forecasting" IEEE, June, 1073-1078.

[12] Philibert C. (2002), "Evolution of mitigation commitments: Certainty vs. Stringency", Draft information paper for Annex I Experts Group

[13] Pindyck R. S. (1999), The long-run evolution of energy prices, The Energy Journal no. 20 ABI/INFOM Global, p 1-27.

[14] Pizer (2002) "Combining price and quantity controls to mitigate global climate change", Journal of Public Economics 85 (2002) 409-434.

[15] G. Prelipcean, M. Boscoianu, “Some aspects regarding the dynamic correlation between different types of strategic investments in Romania after integration”, Proceedings of the 9th WSEAS International Conference on Mathematics and Computers in Business and Economics (MCBE ‘08), Bucharest, Romania, Published by WSEAS Press, p.162-166

[16] G. Prelipcean, M. Boscoianu, “Computational Framework for Assessing Decisions in Energy Investments Based on a Mix between Real Option Analysis and Artificial Neural Networks”, Proceedings of the 9th WSEAS International Conference on Mathematics and Computers in Business and Economics (MCBE ‘08), Bucharest, Romania, Published by WSEAS Press, p.179-184

[17] G. Prelipcean, M. Boscoianu, “The role of predictability of financial series in emerging market application”, Proceedings of the 9th WSEAS International Conference on Mathematics and Computers in Business and Economics (MCBE ‘08), Bucharest, Romania, Published by WSEAS Press, p.203-208

[18] White, H. (1988) "Economic Prediction Using Neural Networks: The Case of IBM Daily Stock Returns" in Proceedings of the Second Annual IEEE Conference on Neural Networks, II.

[19] Yang M. and Blyth W. (2006), Modeling Investment Risks and Uncertainties with Real Options Approach, IEA Working Paper.