Artificial Intelligence based Risk Management Strategies for Trading Portfolios

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1. Abstract

The application of Artificial Intelligence (AI) in the evolving but critical area of risk analysis might not be a comforting idea for many users or market regulators.

But as it will be shown, AI should be looked at as a *process* rather than a black-box product. This is a particular benefit of the type of AI technology that is introduced here, Evolutionary Programming. Evolutionary Programming systems are capable of dealing with very complex inter-relationships of large amounts of data, but are always transparent as a process, enabling the user to look *into* the learning process of the self-learning system, resulting in expressions that can be understood, evaluated, and producing a structure that approximates the nature of the underlying data.

We will show how Evolutionary Programming can integrated into the current risk management process, enhancing the analytical capability without adding unknown model risk to the underlying business process.

The systems and libraries described here are systems developed by Rabatin Investment Technology.

2. Risk Management Requirements of Derivatives Portfolios

2.1 Structure of Risk Analysis for Trading Portfolios

Risk management is a three-tier process consiting of
- definition of risk measurement
- implementation of risk monitoring
- execution of a risk management process

Most modern trading and investment portfolios now include derivatives as components - either to express a certain market view or to hedge or partially hedge positions in underlying instruments, using the risk transfer function of derivative instruments.

What makes derivatives difficult to integrate into traditional portfolio allocation techniques is the separation of allocated capital and allocated risk which occurs when using derivatives: a small amount of capital exposure (generally referred to as “margin”) can be used to create a huge risk exposure. Furthermore, the *type* of risk exposure can dramatically shift during the lifetime of a derivatives position, as is the case typically with options.

Traditional *portfolio allocation* strategies therefore need to be replaced by a principle of *risk allocation strategy* through which an established measurement of risk is used to describe the accepted portfolio risk, which is then utilised by different positions in various derivatives or cash positions.

This results in three problem areas that have to be addressed by the risk management process:

Problem A*:* What is the appropriate measurement for risk?
Problem B: What should be the mechanism to translate the global risk constraint for the portfolio into specific limits and allocations for each trader, position or instrument?
Problem C: As traditional portfolio allocation attempts to optimise the risk/reward profile of a portfolio, how does the employed risk management process affect the portfolio performance?

Problem A is addressed by current risk management practice through the application of the Value-At-Risk (VAR) concept as a uniform risk measurement method across different financial instrument.

But because VAR is not just risk *measurement* provides the basis for risk *prediction*, additional issues arise:

- Do the VAR assumptions sufficiently reflect the behaviour of market prices to represent an acceptable risk prediction?
- How should the risk values for each individual position be aggregated for the entire portfolio?

These issues are difficult to analyse because of a number of aspects:

- We have to attempt to describe the distribution of data (market price data) which we do not fully understand in their nature.
- The aggregation of individual risk values is a non-linear process, as the correlation between instruments (the risk of changes in that correlation) affects the real portfolio risk.
- We are looking to optimise the weighting of potentially a large number individual components under a number of global portfolio constraints (Problem B)
- The integration of the risk management model into the trading or investment strategy, in order to improve the risk/reward profile of a portfolio, requires parallel evaluation of a large search-space of potential decision trees (Problem C)

As it will be shown, these aspects are efficiently dealt with in Artificial Intelligence (AI) systems.

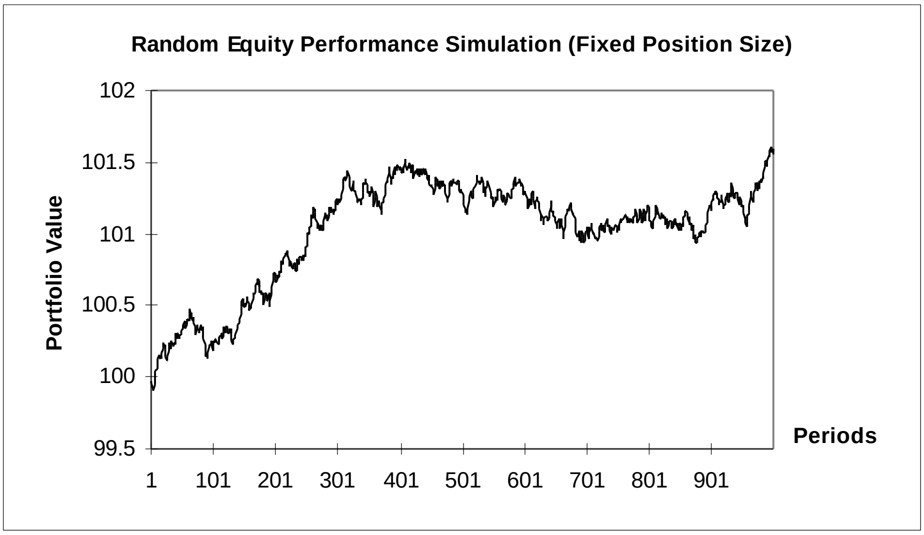
2.2 Effect of Changing Risk Levels when Applying a VAR Risk Model

If we define Value-At-Risk loosely as the percentage of the portfolio that we might lose (at a given confidence limit, within a given time frame), then we are able to define at any point in time the level of risk that we are taking in a portfolio.

That risk is the percentage of the portfolio that we actually *put at risk* for the defined time period. This definition of risk, as previously described, is very different from the asset investment risk view, which defines risk as variance of returns.

As a consequence, the effect of changing risk levels on the portfolio is not just a function of personal preference. It has been shown by [Vince] that for each distribution of returns in a given portfolio (or for a given trading instrument), the total return over a stream of period returns is a function of that percentage level of risk. This chapter focuses on illustrating the concept described in [Vince]. A MS Excel (r) spreadsheet containing the sample data and sample chart is available at http://www.rabatin.com

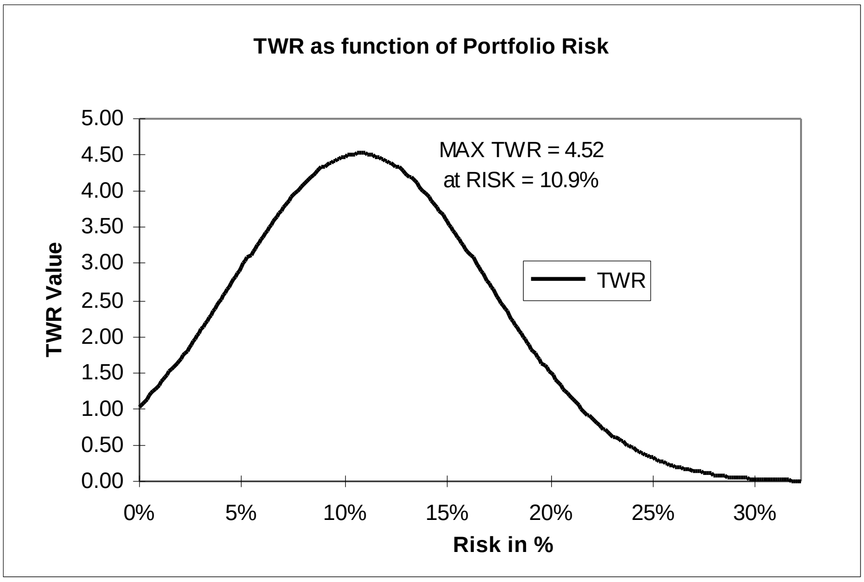
The following chart shows a randomly created, simulated portfolio performance curve over 1000 periods. The probability of profits is 55%



We are now testing the resulting total return of this trading strategy (say, portfolio) against different levels of risk taken. In other words, we are looking for the resulting return of each percentage level of risk that we are taking on the portfolio.
To create this chart, we start with a risk level of 0.1% and continue increasing risk by 0.1 until the total return is -100%, i.e. the entire portfolio value would be lost. We express return as the Terminal Wealth Ratio, which is simply:

TWR = (Final Portfolio Value) / (Beginning Value)

The following graph plots the TWR value against the risk values



As it can be seen, the return achieved on this portfolio increases up to a certain level of risk, finds a single optimum and then, increases in risk result in decrease of portfolio performance. This happens regardless of the defined probability of a “correct” trade as implied in the original performance chart.

TWR can also be expressed as the multiplikative sum of period holing period returns (HPR) over N Periods:

$$TWR = \prod_{n=1}^{N} HPR_n$$

where

$$HPR_t = P_t / P_{t-1}$$

P_t denotes the portfolio value at time t.

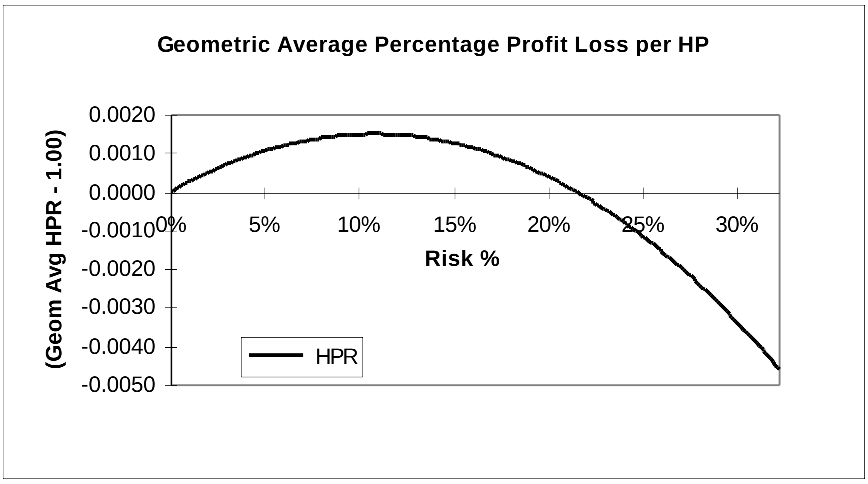
To find the "growth factor" for a portfolio holding period, we can calculate the geometric mean of all holding period returns HPRs, which is:

$$G = TWR^{1/N}$$

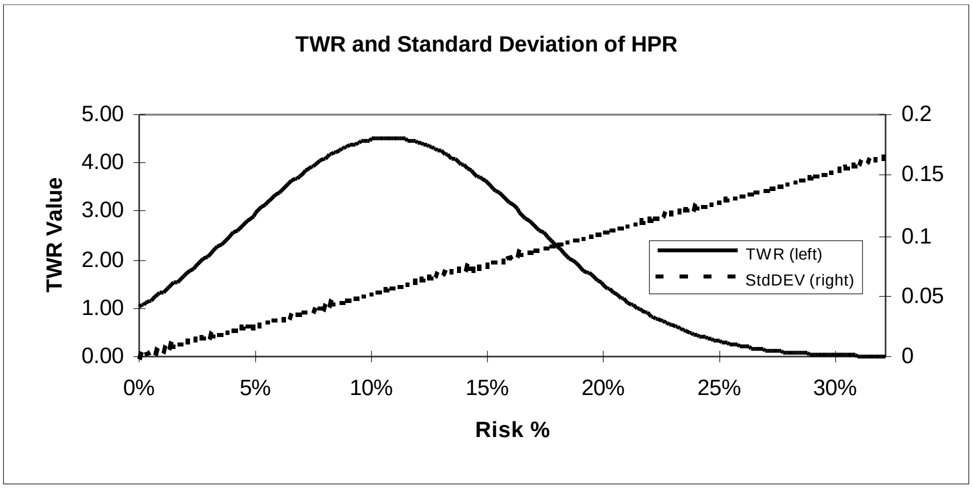
G ... Geometric Average HPR
N ... Number of Periods

To correctly calculate this value over a portfolio, not individual traders, mark-to-market equity changes have to be used and returns have to be weighted according to the weighting of the instrument within the portfolio.

The following chart plots the geometric average return against different risk levels.

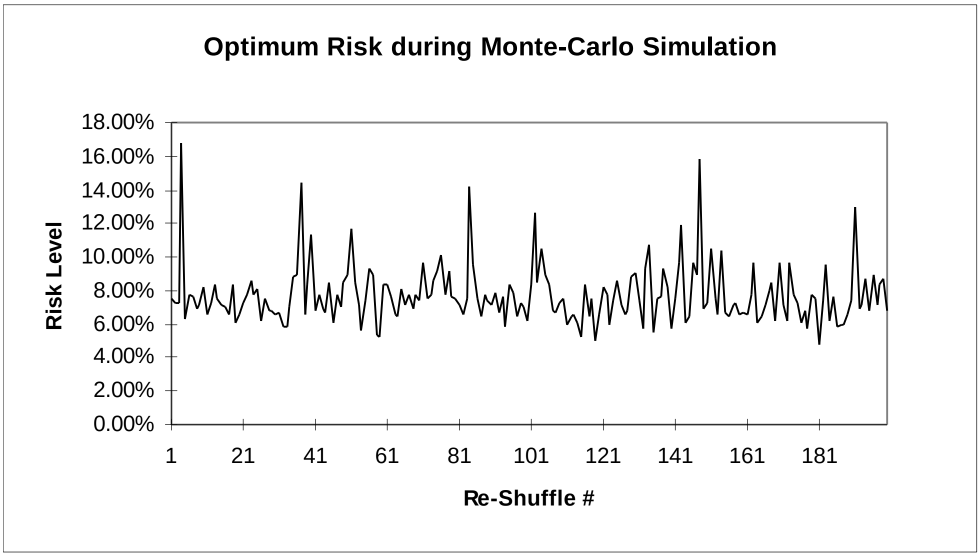


Note that the standard deviation of HPRs is a linear function (against the risk):



As the optimum risk level changes with a change in the distribution of returns, we can use a Monte-Carlo simulation, i.e. a number of "random reshuffles" of the stream of returns to better estimate the risk inherent in the portfolio (or instrument) trading strategy.

The following charts plots the different optimum risk levels for several randomly generated variations of the distribution of returns.



This type of simulation offers a basic understanding of what risk exposure the portfolio is set at, providing the basis for an improvement of the process using Artificial Intelligence systems.

3. Relevance of Artificial Intelligence Systems to Risk Management

3.1 Evolutionary Programming Systems

As introduced in the previous chapter, the analysis of portfolio risk has to take into account a large number of possible data inter-relationships (to create a model for aggregating portfolio component risk) and the resulting risk level has a defined effect on the portfolio performance we might expect from this risk to be taken.

Conventional analysis methods and conventional computer programs are limited in the amount of data inter-relationships or decision uncertainty they can cope with. This is due to the fact that each data relationship such a system should analyse has to be first defined in some ways by an analyst or programmer.

Artificial Intelligence (AI) systems use a different approach. The general benefit of an AI system is its ability *to develop rules or exhibit behaviour, beyond what has been explicitly programmed into the system*. Through that ability, AI systems are able to generate new knowledge (by extracting hidden information from data) and to enhance and evaluate existing knowledge (by building rule systems composed of information provided by a human expert).

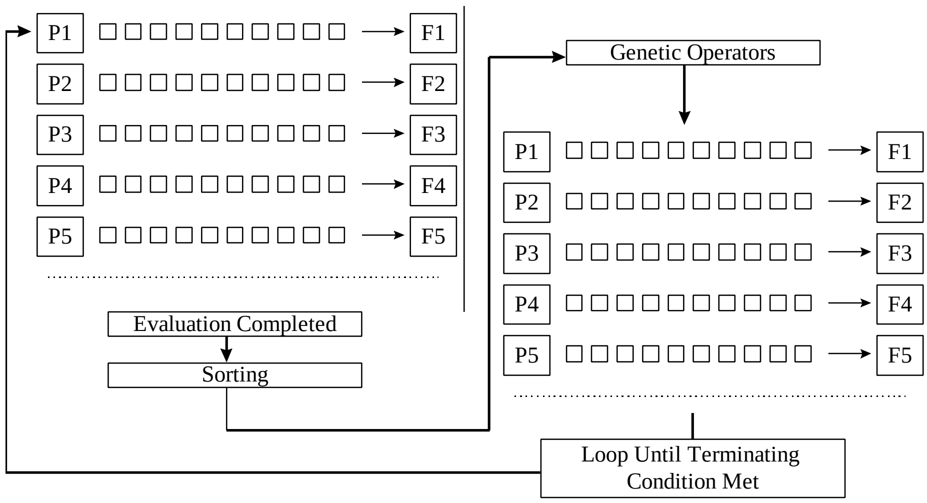
Among the huge number of AI technologies currently researched, *Evolutionary Programming* has emerged as the area with the fastest growing interest from AI technology users.

Evolutionary Programming borrows principles from the natural evolutionary process to develop computer programs. The most important principle is the concept of "survival of the fittest”. Translated into a programming model, this means that the algorithm always deals with an array of potential solutions, rather than attempting to optimise one single structure (as do, e.g. Neural Networks). This array of candidate solutions is referred to as “population” and after one population is evaluated, a competition between the solutions is introduced which will lead to higher fitness individuals (i.e. solutions closer to the desired result) being more likely to survive in a new population, i.e. a new “generation”.

In the process of creating new generations of solutions, previous solutions are combined in so-called “cross-over” operations, which is a method to combine sections of particularly encoded programs to create new solutions, consisting of components of higher fitness individual solutions.

The following chart illustrates the evolutionary process:

P ... denotes a member of the population
F ... denotes the value of its fitness, i.e. the ranking of the result of the created rule set as to the desired function.



The “Terminating Condition” is the limit we set to the learning process, which is either a desired value for the calculation (e.g. the optimum risk level for a given distribution of returns) or a general limit on time and resources made available to the learning process.

The most important of Evolutionary Programming are Genetic Algorithms (GA) and Genetic Programming (GP), which we both use where appropriate for the specific problem domain. Genetic Programming lends itself well for “symbolic regression” analysis, which builds formulae, based on mathematical and logical operators, that create the best solution to the formulated problem. GP systems can build any possible structure as a result to a particular problem and are therefore capable of delivering solutions which are very similar to the nature of the underlying problem.

GA systems are better suited to optimise structures within defined limits of complexity (e.g. if a certain type of solution is sought, for instance, based on an existing model), combined with a very large space of data that has to be searched. GA systems also perform well when very different types of data analysis or decision simulation have to be integrated into one single AI learning process.

Genetic Algorithms operate through an encoding of the solutions into binary strings, which are manipulation similar to the way cross-over is performed in nature on chromosomes (hence the term “genetic”), whereas Genetic Programming operates directly with functions and operators.

3.2 Knowledge Discovery using Genetic Algorithms and Genetic Programming

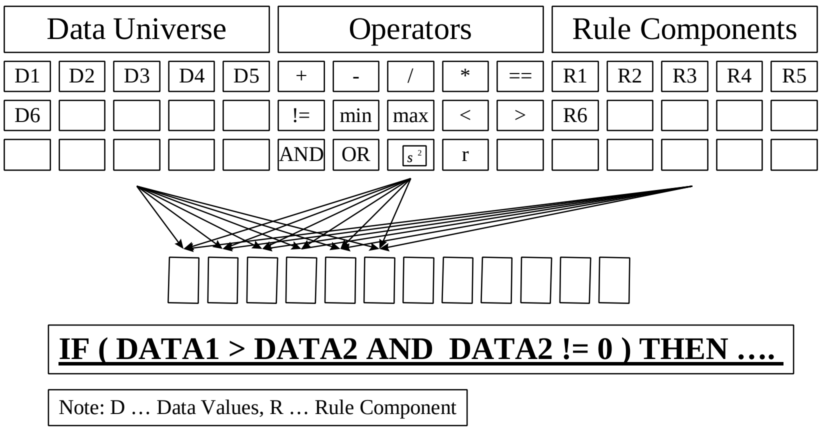
GAs and GPs share the ability (although they work through different algorithms) to create rule structures based on the complex combination of simple mathematical or logical operators.

The process can be enhanced and customised by adding functions, which are known to be relevant to the knowledge base, to the array of operators the EP system can select from in creating a solution to the question posed.

The process can also be customised by adding rule sets which restrict the possible solution space or which implement constraints on the result, as to allow only a range of risk levels to be calculated (typically by restricting the maximum allowed risk level).

The advantage of evolutionary programming technology is the ability to implement user defined constraints into the learning process, and not just impose on the final result. This will create a system that is trained to best perform its function under the given constraints. This constraint requirement is particularly important for any risk analysis where constraints have to be met.

The following graph shows an overview on how an evolutionary programming system dynamically creates a rule using a range of available components:



The learning process will through a structured random process combine the components availabel to the process in order to create an expression that is aimed to create a solution improving towards the target function/

3.3 Self-Learning (Adaptive) Systems for Risk Decision Simulation

Adaptive systems are an extension of an existing AI model, based on two concepts:

- frequent re-training of the models to include new environment data
- historical simulation of the high frequency training process to measure the adaptive capability of the model

Adaptive systems should not be implemented using constant values or constant factors, because these factors would represent an optimisation of the numerical parameters, whereas adaptive systems should aim at optimising the logical structure (or syntax) of the solution.

In risk management systems, this would apply to assumptions we would make on time horizons of investments or assumed volatility's of returns.
Evolutionary Programming is better suited to create adaptive structures than other AI technologies because of their ability to create understandable mathematical and logical syntax as a solution, based on the operators and functions provided. EP systems can therefore incorporate the adaptive behaviour into the model, without having to rely on pre-processed data (as neural networks do).

Evolutionary Programming also allows the integration of different types of rule sets into the learning process, thus enabling the system to simulate the decision process, rather than performing only the analysis process.

The most relevant type of decision that is to be made from a risk management point of view is the allocation of risk to different traders (or investment funds), positions or instruments.

This decision simulation can be made part of the available functions that are accessible by the learning process. By design, the learning process can be forced to conclude the created solution with a component from possible risk decisions, which then automatically connects a certain type of formula (to calculate risk) with a certain type of decision (to manage risk by allocating or de-allocating).

4. Application of AI/Evolutionary Programming to Risk Measurement / Risk Monitoring

Evolutionary Programming can be summarised as self-programming structures that allow creating complex analysis models without the need to explicitly program such models. We can therefore use EP as a tool-set to detect those data inter-relationships and those risk-factors which we are not aware of in our analysis process.

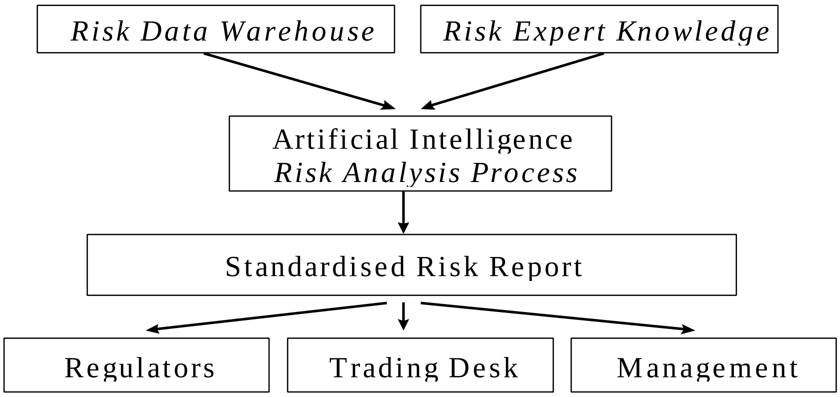
The capability of EP systems to use user-specific functions and formulae, as well as a-priori defined rules and constraints enhances the use of EP in risk management.

In the risk analysis process this means that we can create an Artificial Intelligence process, which incorporates

- ⇒ our own definition and understanding of risk (say, the VAR model)
- ⇒ our own adjustment for the used level of risk (say, a Monte-Carlo process)
- ⇒ our own additional constraints that we want to impose upon the result of the AI system

into the learning process and can therefore be integrated into the existing business process.

The following chart provides an overview how the Artificial Intelligence risk analysis process can be integrated into any existing risk analysis process, integrating both the existing intellectual database of risk management as well as the physical "data-database" of available risk data (market prices, accounting).



Through the additional layer of applying the risk constraints during the AI process, the result of the risk analysis process can be used to present relevant data to management, trading desk and to regulators, as would be the central bank for banks in most countries or other relevant regulatory authorities.

5. Integrating Market Timing and Risk Management

5.1 Aspects of Investment Decisions

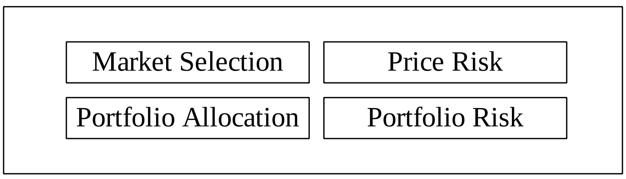
Market Timing is the investment or trading strategy, which is essentially the decision to buy or sell a certain instrument.

Typically, the market timing decision is separated from risk management decisions, mostly because the person involved in making investment decisions is not made aware of the risk profile of the entire portfolio (or the sum of individual portfolios, in a fund, for example).

As was shown in the introductory chapter however, every investment decision taken under risk has some kind of Value-At-Risk value attached that relates to the portfolio as a whole, and resides somewhere on the landscape of possible risk/return values at any given distribution of returns.

As a result, treating the risk management process as an overlay to the market timing strategy might have results which are not predictable because of the affect the risk management decision has on changing position sizes, therefore resulting in a different shape of distribution of returns.

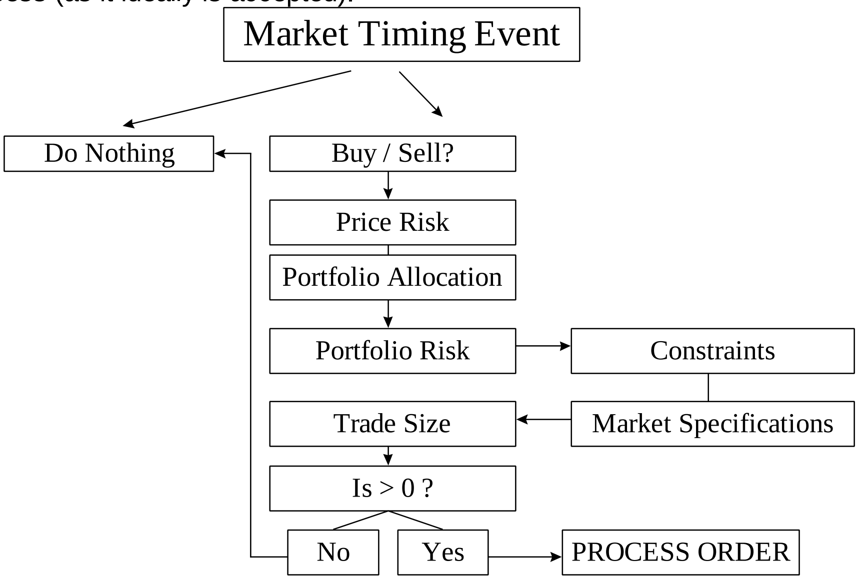
Dimensions of an Investment Decision



Each trading or investment decision has four “dimensions” (besides the decision to either buy or sell a given instrument). The dimensions are always attached to the decision and can always be measured and evaluated against constraints. As such, Artificial Intelligence systems can be applied in each of those areas to perform all or part of the calculations, resulting in a value which then can be processed as part of the standard business process or accounting system.

5.2 Model Process For Investment Decisions integrating Risk Management

The following graph provides an overview of the process of the investment decision, as it would appear when risk management and the market timing decision are integrated into a single process (as it ideally is accepted).



The "market timing" event is any event that would trigger a decision to be made, such as the change in a country's interest rate policy or change in a company's investment policy. For an intra-day foreign exchange trader, such a trigger could be a technical signal on a charting system or information from the marketplace.

In the following process, the key to integrating the risk analysis into the decision process (hence creating a risk management strategy) is the evaluation of the overall risk constraint before the trading decision is translated into an order that is processed at the trading desk.

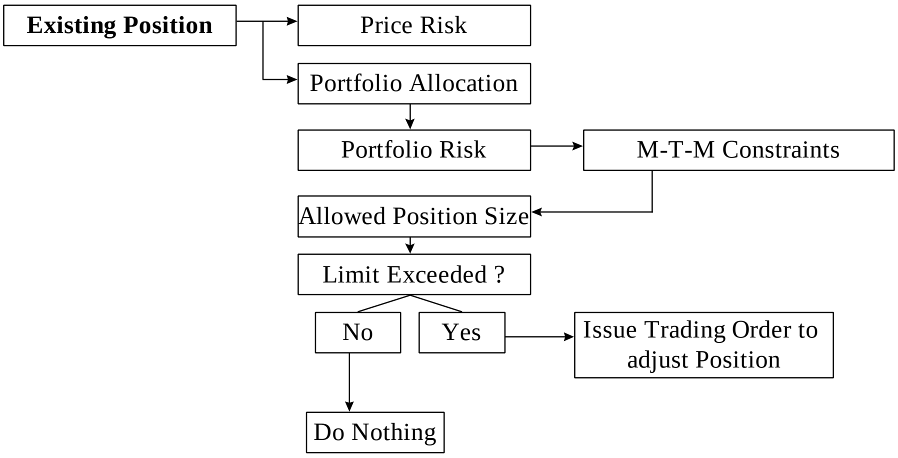
"Price Risk" here is used for risk measurement referring to a single instrument. In combination with the available allocation, a portfolio risk value is calculated, which is then checked against the constraints in place. Controlling market specifications adds an additional layer of control, such as positions constraints (large position constraints in futures markets) or other non-risk constraints. The result of the calculation is the available position size which can be taken in the market at that moment. Only if the possible trade size is greater than zero, clearly, the trade can be executed, otherwise no position is being taken.

What are the benefits of that model ?

- The entire process can be automated in one system of approval for all trading decision made by individual traders or fund management, integrating compliance procedures and risk management into a single-step function at the trading desk.
- The use of Artificial Intelligence systems to perform the risk analysis is hidden from the trader as the trader only receives the result of the calculation.
- The trading decision of each individual trader or fund manager is always checked against the entire portfolio at a mark-to-market level
- The implementation of this process model is scalable, i.e. one trading desk or fund management group at a time can be integrated into the process model

At each mark-to-market evaluation, the same type of process is executed, only that the basis for the process is not a new investment decision, but an existing position in the market. The constraints applied to the position ("mark-to-market constraints") might also be different to the initial constraints.

The following graph shows an overview of the process at the point of mark-to-market.



Again, through the use of the systematic process, the resulting decision (to adjust the position or not) is passed on to the trading desk, although the actual process of calculation (most likely a combination of conventional and artificial intelligence methods) is not performed at the trading desk.

5.3 Adaptive Portfolio Trading (APT) Framework

The Adaptive Portfolio Trading Framework (APT) is the development framework Rabatin Investment Technology has developed to integrate the different types of decision required during a managed risk process on a diversified portfolio.

Evolutionary programming has established a leading position in Artificial Intelligence research and will continue to affect more areas of application. The APT framework makes use of this technology by providing a framework for attaching the AI process to different aspects of the investment, allocation and position management decision.

The APT framework provides an implementation of the process model for creating trading strategies, as well as integration of market timing models into the risk management process.

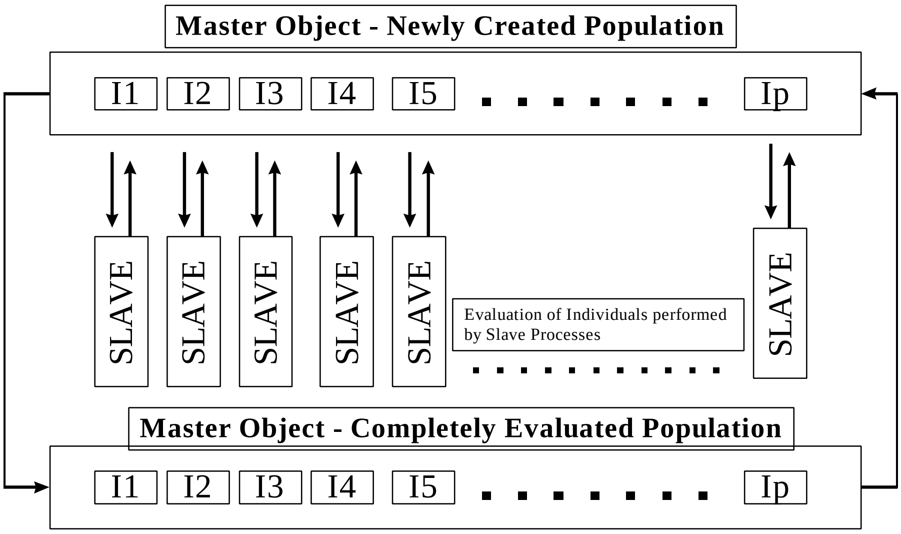
6. Managing the Computational Workload: Distributed/Parallel Processing in Evolutionary Programming

Due to the large number of factors and data inter-relationships, the power of a single workstation is unlikely to suffice as a tool to develop these models.

We present an overview of the distributed programming model we have implemented within our Genetic Algorithm and Genetic Programming libraries, with are packaged into the Evolving Programming Library (EPL), a set of C++ class libraries which form the basis of the evolutionary programming applications.

EP lends itself very well to distributed or parallel processing due to the (potentially) parallel processing of an array of candidate solutions to the given problem.

The following chart describes the architecture we use for the distributed process. Distributed Processing differs from client/server as client/server relies on the processing capability of the server which is accessed by a number of clients. Distributed programming works in the opposite direction: because the central process is not capable of performing all calculations, it distributes the workload to a number of other workstations that each perform a share of the total task and send the result over the network back to the central process. The common term for this architecture is “master/slave”.



The master process will always evaluate the entire population of results, where the actual calculations for each individual candidate solution (i.e. risk model, trading model ...) is performed by the worker thread or slave process.

Because the main computational requirement lies with the evaluation of each candidate solution, the overhead created by the distributed process (due to the co-ordination of slave processes and the need to send objects across the network) is minimal compared to the performance gain created by this architecture.

This model enables us to provide solutions for huge number of data and calculations, which could not be implemented in a single threaded process.

7. Conclusion

We have described the underlying concepts of a new generation of Artificial Intelligence systems, based on Evolutionary Programming. As we have shown, the specific requirements of modern trading portfolios require improved analytical and process modelling systems, which can be found in artificial intelligence systems.

For the practical implementation of such systems it is important that they integrate into an existing business process and that the AI system does not present black-box calculations, which would only add to the risk already inherent in any modelling process.

Genetic Algorithms and Genetic Programming provide that transparent AI process that is needed for effective AI based risk analysis and modelling. Further sample charts and test-bed applications are available at our web site http://www.rabatin.com or by contacting research@rabatin.com

<u>Notes</u>

[Vince] Vince, R (1990), Portfolio Management Formulas, New York, John Wiley & Sons
Vince, R (1995), The New Money Management, New York, John Wiley & Sons