

# SIMULATION AND OPTIMIZATION OF AUTOMATED TRADING STRATEGIES

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## ABSTRACT

This article introduces readers to the problematic of the short-term speculations on financial markets in context of the intelligent systems. This article describes how the simulation and optimization techniques can be used for a composition of the robust automated trading systems.

## 1. INTRODUCTION

The good question is if a system based on the artificial intelligence is able to analyze market behavior more precisely than a flesh-and-blood trader, and to generate more reliable trading recommendations. If the trader evaluates market behavior detachedly, he is able to achieve much better trading results. The point is that traders are rarely psychologically detached from decisions which they take, because they are handling with their own money. Because of this, the trading is considered as an intellectually simple, but psychologically difficult activity. The system based on an artificial intelligence is the right choice for this kind of activity, because it lacks psychological aspects of the human nature.

## 2. AUTOMATED TRADING STRATEGIES

As we have said, the advantage of the mechanical trading systems is that they provide crisp signals and eliminate psychological aspects of the trading. Let's consider a simple trend-following parametric strategy which takes entry decisions according to a crossover of two different exponential moving averages (abbreviated EMA). The strategy exits are defined just by the money management rules (profit targets and stop-losses). A core of the strategy can be expressed by the following rules:

1. If  $EMA(n)$  crosses  $EMA(m)$  from the bottom then enter long position
2. If  $EMA(n)$  crosses  $EMA(m)$  from the top then enter short position
3. Place the profit target  $p$  ticks above/below the entry price
4. Place the stop-loss  $s$  ticks above/below the entry price

The  $EMA(n)$  is an exponential moving average with the period of  $n$  bars. According to the strategy below, the automatic trading system has four different parameters:  $m, n, p, s$ .

In order that markets employ very dynamic and heterogeneous behavior, every automated trading system sustains successful only for a limited period of time. Because of this, traders must manually choose indicators and parameters to use as a basis of the trading strategy. In such cases, a deep simulation of the trading strategy on historical data would be useful.

Alternatively, we can involve fuzzy logic into the automated trading strategy to improve its robustness.

### 3. SIMULATION OF TRADING STRATEGIES

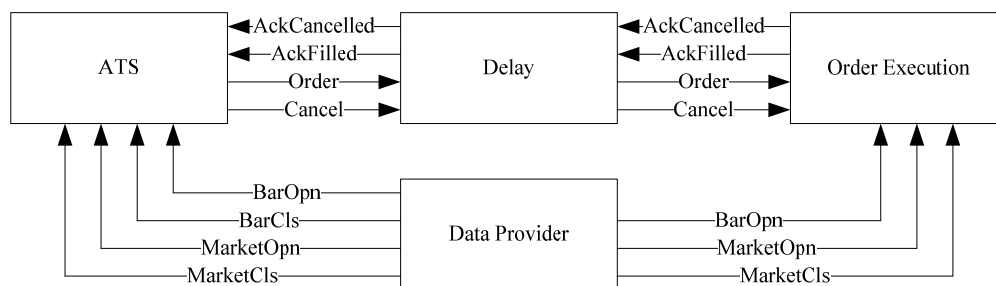
The impact of the automated trading strategies can be studied on a model of trading environment based on historical data. This approach is often referred as the *paper trading*. The modeling and simulation allows traders to perform what-if analyses on the parameters and comparative tasks on different strategies.

The DEVS model approximates trading environment and consists of the *Automated Trading System* (abbreviated *ATS*), *Order Execution* and the *Data Provider*. The *ATS* implements behavior of the trader or the automated trading system, respectively.

The *Data Provider* component is an abstraction of the functionality provided by a security exchange or a broker. It has only one purpose, to provide a stream of price quotes. In the reality, the security exchange provides real-time quotations of the prices asynchronously from any time frames, and it is a customer's interest to react to them as quickly as possible.

The *Order Execution* component simulates execution of orders entered by the automated trading system. This component is also only an abstraction that covers functionality provided by a security exchange or a broker. In contrary to the real brokers, this component simulates only an execution of clients' orders and doesn't tend if the client has appropriate financial resources needed for the trade.

The trading environment involves various types of time and price skews. The communication flow employs orders, cancels, acknowledgements and price quotes. The figure 1 illustrates basic arrangement of the model's components.



**Figure 1:** The coupled DEVS model of the trading environment.

### 4. OPTIMIZATION OF TRADING STRATEGIES

Modeling and simulation of automated trading strategies allows traders to repeatedly and comparatively perform various strategies on the same data. Because of this, it allows us to perform also a wide spectrum of optimization tasks. The optimization engine finds the best combination of signaling system's parameters in order to maximize the fitness function of

the trading strategy. There are many possible fitness functions, but we use the function that respects both the absolute outcome as well as robustness of the trading strategy (Eq. 1):

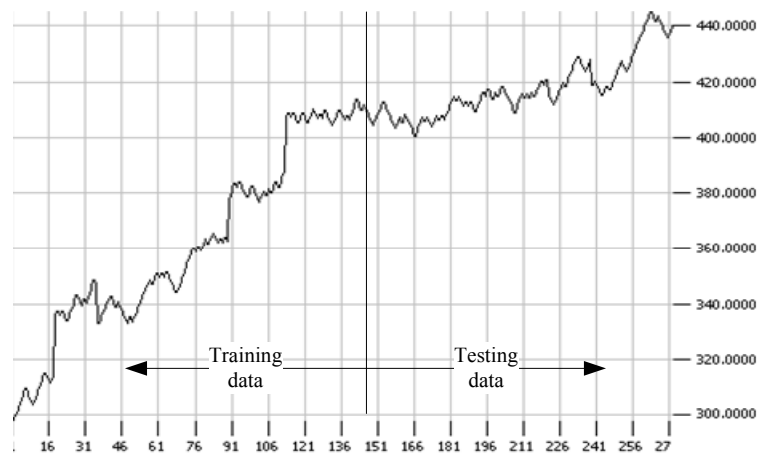
$$\text{fitness}(\text{params}) = e - a, \quad (1)$$

where  $e$  is a highest equity that the strategy produced and  $a$  is the highest drawdown of the trading account.

If we run the strategy proposed in Section 2 on an intraday E-mini Russell 2000 futures market between 15<sup>th</sup> of August 2007 and 31<sup>th</sup> of the same month, the genetic algorithm returns a following combination of parameters as the best solution:

$$n=7, m=14, p=5.75, s=5$$

Figure 2 contains the equity curve of our strategy. This equity curve contains trades performed on the training data (the data on which the optimization algorithm runs) and on the testing data which weren't available during the optimization.



**Figure 2:** The performance of the trading strategy simulated on training and testing data.

## 5. CONCLUSION

The strategy has been trained on the data between the 15<sup>th</sup> of August 2007 and 31<sup>th</sup> of the same month. After that, it has been tested on the out-of-sample data until the expiration date of 21<sup>th</sup> of September 2007.

Our strategy wasn't able to keep its previous performance on the testing data. The strategy generated 142 in-sample and 130 out-of-sample trades with total returns of 27.32% and 10.45%, respectively.

## REFERENCES

- [1] Martinsky, O.: Intelligent System for Generating and Analysis of Trading Recommendations on Financial Markets, master thesis, FIT BUT Brno, 2009
- [2] Russel, S. and Norvig, P.: Artificial Intelligence, a Modern Approach, Pearson Education 2003, ISBN 978-0-13-790395-5
- [3] Fishwick, P.: Simulation Model Design and Execution, Prentice Hall 1995, ISBN 978-0-13-098609-2