Evolutionary Algorithms in Trading: A Transparent Strategy

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Abstract

In the age of prevailing black-box trading strategies, there is a vacuum for transparent methodologies that provide insights into the market. This paper introduces a novel and underutilised framework of Evolutionary Algorithms (EAs), to optimise and select neural network models, to better understand the decision-making processes. Iterative selection, arithmetic genetic crossovers and genetic mutations are used to achieve improvements through successive generations. The results on data simulating the market indicate a marked amelioration in trading performance over time. An analysis of the dominant genes reveals influential neural network connections that indicate the relative importance of the inputs while explaining the network logic. The study concludes that integrating EAs with neural network could be explored further as a viable tool to bridge the gap between opaque algorithmic solutions and decision-making rationale.

1 Introduction

In the ever-evolving world of financial markets, there has been a meteoric rise in the proportion of algorithmic trading strategies being implemented [3]. However, despite their prevalence, the usage of black-box algorithms has left behind a blind spot in the interpretability of these algorithms [1]. Such models, often powerful, do not help in revealing underlying patterns in the market in which they can be implemented. To tackle this problem, Evolutionary Algorithms (EAs) are proposed as an alternative.

EAs offer an unconventional way of optimising neural networks. Mirroring nature, EAs utilise the rule of "survival of the fittest" to come to an optimum solution. This approach preserves the power of the neural networks while aiding interpretability. Traditional methods in comparison such as Recurrent Neural Networks and ARIMA, fall short in transparency and adaptability respectively [2].

This exploration introduces an EA-driven environment for trading decisions based on real-time price fluctuations. The paper examines the structure and function of EAs and explores the evolutionary journey of a population, revealing enhanced trading outcomes over generations. The results highlight specific genetic traits, represented as neural connections, contributing to success.

2 Methodology

A brief introduction to the environment set-up, the implementation of EAs and gene encoding will be given in this section.

2.1 Environment

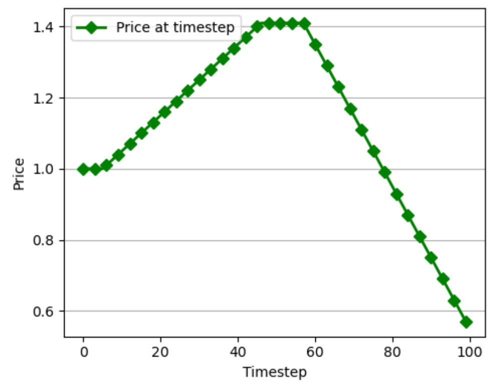

Figure 1: The price of a trading product over a hundred timesteps in the environment. The markers denote every third timestep.

In the heart of this study lies a simulated trading environment, where a model engages in the buying and selling of a single product. The product's price is subject to fluctuations (as seen in Figure 1), representing market dynamics at each discrete timestep. The primary goal of the model is to leverage these price movements to maximise profit through strategic trading actions. Commencing with an initial capital of 20 currency units, the model at each timestep choses among three possible actions: to buy the product, to sell it, or to abstain from trading (do nothing). The aim of the model is to maximise the rewards, which is the total value of the money and the products at the price for current timestep. In the next subsection, the encoding of a possible model for the environment into a gene is explained.

2.2 Encoding Solutions as Genes

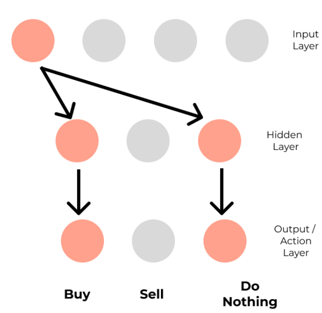

Figure 2: A schematic representation of a neural network used as a potential solution in the trading environment. The network comprises an input layer, a hidden layer, and an output layer. Each colored line represents a gene-encoded neural connection, with the weight of the connection determining its influence on the subsequent neuron's activation.

To reiterate, in this study, a neural network model is built with only a few connections. Here, a gene is an abstraction of a neural connection, that contains weight that quantifies its influence on the network's decision-making process. Figure 2 shows a neural network where each visible connection, shown with solid black lines, symbolizes a gene. These genes collectively form the genotype of an individual in our evolutionary landscape.

The neural network's selective connectivity is critical for the framework. This allows us to hone into the connections that really matter while discarding the other ones.

2.3 Evolutionary Algorithms

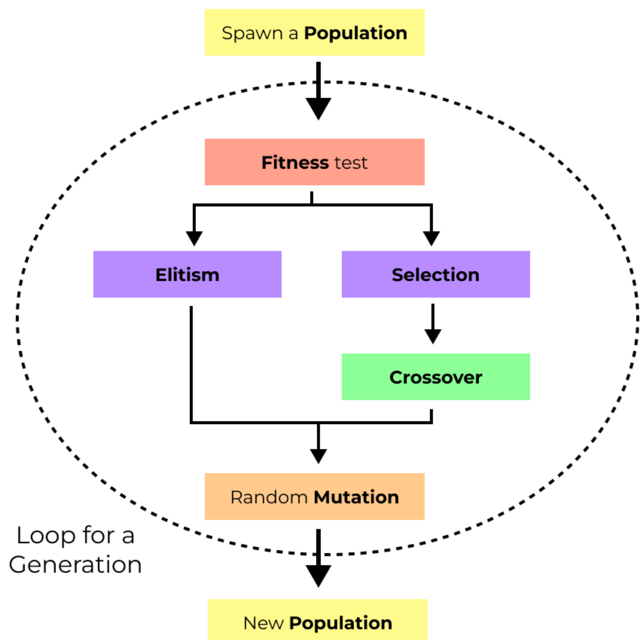

Figure 3: Schematic of the Evolutionary Algorithm workflow detailing the cyclic process of population evolution in a trading context. The steps inside the dotted line - fitness test, elitism, selection, crossover, and mutation constitute the core iterative loop that drives the evolution of trading strategies across generations.

For the environment discussed earlier, a population comprising a number of possible solutions is spawned as shown in Figure 3. Next, the fitness of each of the members is measured. A fixed percentage (20%) in this project of the top performing species are copied over to the next generation. Next, to select the rest of the population, mini-tournaments between members are held. For example, in a tournament of size 4, the best out of these four individuals is selected for crossover. Another candidate for crossover is selected from a similar tournament with four other individuals. Furthermore, a crossover process occurs where the parts of both the genes are taken to produce the offsprings (two offsprings are produced here).

During this crossover, the new weights are produced as shown in the following equations:

$$x = \lambda \cdot a + (1 - \lambda) \cdot b \tag{1}$$

$$y = (1 - \lambda) \cdot a + \lambda \cdot b \tag{2}$$

Here, λ is a randomly selected value within the interval [0, 1], and a and b represent the parental weights contributing to the offspring's genetic makeup, denoted by x and y.

2.4 Parameters for the Run

For the described environment and price variants, a population of 300 individuals representing varied solutions was run for a 100 generations.

3 Results

The evolutionary algorithm's success is quantified by the performance metrics of the neural network models over generations. An upward trend in mean rewards, as shown in Figure 4, indicates a successful adaptation and improvement in trading strategies developed by the models.

3.1 Performance over generations

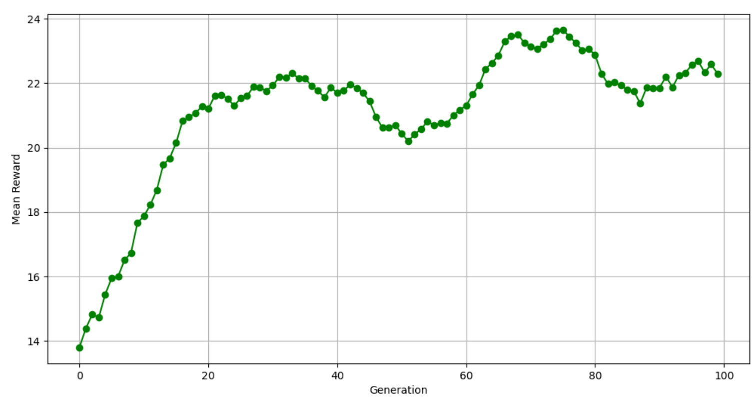

Figure 4: The average performance metrics of the neural network models across 100 generations. The trend line showcases the progression of mean rewards earned by the models, illustrating the efficacy of the evolutionary process in enhancing trading strategies over time. The increasing trend signifies a continual improvement in the models' capability to maximise profits within the simulated trading environment.

The performance of the models over generations is depicted in Figure 4. A noticeable trend is the initial rapid increase in performance, which suggests that significant improvements can be made in the early stages of the evolutionary process. The subsequent plateau indicates the convergence towards an optimal strategy within the constraints of the neural network architecture and the environment. It is also important to note that the last generation is not the best performing generation on average. However, the best performing model from the last generation will be used to analyse the trading algorithm found.

3.2 Case Study: Best performing Model

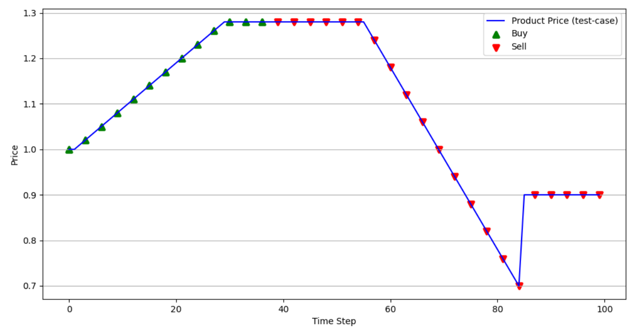

Figure 5: Decision-making pattern of the top-performing neural network model in a test simulated trading environment (different to training environment). The plot juxtaposes the model's chosen actions—buy, sell, or hold—against the price fluctuations of the trading product. This visualization provides insights into the model's strategic timing for transactions, correlating its buying and selling decisions with market trends, and thereby demonstrating the model's predictive and adaptive capabilities.

As seen from Figure 6, the model buys in the upward trajectory and sells when a downward trajectory might be approaching. This is the optimum solution for our case. The model's ability to buy during a price increase and sell during a decrease demonstrates its successful pattern recognition and prediction capabilities, leading to profitable trading decisions.

3.3 Gene Analysis

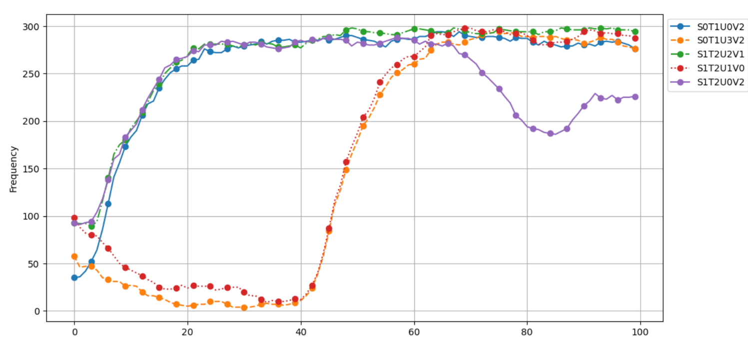

Figure 6: Evolution of gene frequencies across 100 generations, highlighting the adaptive significance of specific neural connections within the population. Each line tracks the prevalence of a particular gene, providing insight into the behaviours that are retained or developed over time.

The investigation into gene frequencies within the population's neural networks is pivotal for understanding the traits that confer a trading edge. Table 1 catalogs the most prevalent genes, which correspond to the neural connections that consistently contributed to higher trading profits.

3.3.1 Gene Naming Nomenclature

The labeling of genes in the context of neural networks for this study follows a specific nomenclature where each gene represents a connection between two neurons in different layers of the network, along with its weight. Here's how the labeling works:

The letter 'S' stands for the source layer from which the connection originates. The letter 'T' refers to the target layer to which the connection leads. The letter 'U' is followed by a number that identifies the specific neuron in the source layer. The letter 'V' is followed by a number that identifies the specific neuron in the target layer. So, for example, a gene labeled as 'S0T1U0V2' describes a connection where:

'S0' indicates the connection starts from the first layer (input layer). 'T1' indicates the connection goes to the second layer. 'U0' specifies it's the first neuron in the input layer. 'V2' specifies it's the third neuron in the second layer. The weight of this connection, which determines its influence on the network's output, is encoded along with this gene label.

Gene	Frequency
S1T2U2V1	2948
S1T2U1V0	2944
S0T1U0V2	2891
S0T1U3V2	2883
S1T2U0V2	2518

Table 1: Frequency of dominant genes observed in the population over 100 generations.

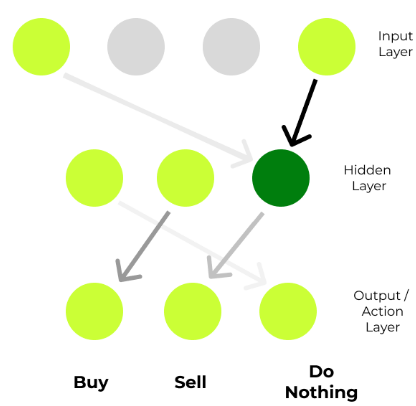

Figure 7: The neural network topology at the final generation, with the top five gene connections color-coded to indicate the weight magnitude. Darker shades represent stronger connections that have been consistently selected for their contribution to profitable trading decisions. This map provides a visual summary of the network architecture that evolved as the most successful through the simulation.

The gene frequency analysis, as shown in Figure 7, reveals which connections in the neural network were most influential in the trading decision process. Genes corresponding to these connections became more prevalent over time, suggesting their significant role in the models' improved performance.

3.3.2 Interpreting Gene Performance

Figure 7 aids in discerning which inputs and neural combinations are the most instrumental in the decision-making process. The genes S0T1U0V2 and S0T1U3V2, for instance, highlight the significant influence of inputs at positions U0 and U3. The prominence of these genes indicates that the corresponding inputs are strong predictors for the model's trading decisions. Similarly, the genes S1T2U2V1 and S1T2U1V0, which form connections between the first and second layers, emerged as effective combinations for generating profitable actions. These connections were repeatedly selected through the evolutionary process, underlining their contribution to the neural network's success.

Hence, we are able to identify that the inputs received at both the first and fourth neurons of the first layer are important. Apart from this, we also understand their relative importances are shown by the strength of the connections in Figure 7. We can also identify that these inputs are strongly linked to the timing of 'sell' action in the model. By further considering more than top 5 genes, more information about the 'buy' action can be understood. For instance, the second neuron in the hidden layer is strongly linked to this action. Hence, the gene linking this action with the input would inform us of which input is important to take this call.

4 Conclusion

Hence, we have understood some inherent patterns in the data we have alongside informing ourselves about the decision making process taken by the model. So, the application of evolutionary algorithms to market trading presents a novel approach to understanding and predicting market trends. This study has demonstrated the viability of using EAs as a transparent alternative to traditional black-box models.

Further optimization of the weights in the neural network models could be achieved by introducing elements of gradient descent. This approach could refine the adjustments of weights, leading to potentially more precise and efficient trading strategies. Moreover, experimenting with a more varied population in the evolutionary process could enhance the robustness and diversity of the solutions. Ultimately, the integration of these advanced optimization techniques with the demonstrated evolutionary framework could provide a more comprehensive and potent toolset for financial market analysis, potentially bridging the gap further between automated trading and decision-making transparency.

References

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