Study on Stock Trading and Portfolio Optimization using Evolutionary Computation

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Background-Evolutionary Computation

- Evolutionary Computation (EC) is well-known for producing the solutions in optimization problems based on change, composition and selection.

**Adaptability**: EC does not have much mathematical requirements about the optimization problems due to the evolutionary nature.

**Robustness**: The use of evolution operators makes EC very effective in performing global search, while most of the conventional heuristics usually perform local search.

**Flexibility**: EC provides us a great flexibility to hybridize with domain-dependent heuristics to make an efficient implementation for a specific problem.
Background-Evolution and RL

- **Evolution**: Many individuals work and better ones are selected after task execution.

- **Reinforcement Learning (RL)**: One individual works and learns action rules during task execution.

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- Diversified search
- Offline learning

- Intensified search
- Online learning
Evolutionary Process-GNP

Generation 1:
- Individual 1 (GNP1)
- Individual 2 (GNP2)
- Individual 3 (GNP3)

Generation 2:
- Individual 1 (GNP1)
- Individual 2 (GNP2)
- Individual 3 (GNP3)

Generations...

Best GNP stock trading model

Best Individual
Research Topics

Chapter 1

- Efficient stock trading rules using Genetic Network Programming with reinforcement learning

Chapter 2

- A portfolio optimization model using Genetic Network Programming with control nodes
Chapter 1: Trading Rules on Stock Markets Using Genetic Network Programming with Sarsa Learning

- **Judgment node**
  
  ---Each node judges the information in an environment

  Ex.)
  
  - less than 0.3
  - more than 0.7
  - otherwise

- **Processing node**
  
  ---Each node determines an action

  Determine whether take buying action or selling action
Role of Evolution and Learning

- **Evolution**: Create structures by crossover and mutation
- **Sarsa learning**: Learn (update) parameters in nodes and determine which sub-node to be selected

**Action**
Select a sub-node used for taking action

**State**
Activated node

Q: action value (Q-value)
Judgment Function 1 - Technical Index

- An example of technical index (Toyota Motor)

**MACD**: Moving Average Convergence and Divergence

The difference between the smoothing average of the stock prices in 12 days and 26 days is called **MACD**.
Judgment Function 1 - Technical Index

- **Importance Index (IMX)**

Why we propose Importance Index as the judgment function?

- Since there are too many kinds of technical indexes in the stock market and different index has different calculating method, it is difficult to compare with each other.

- With IMX function, we can get the IMX values of different indexes under the same criterion.
Judgment Function 1 - Technical Index

- Importance Index --- RSI (Relative Strength Index)

IMX = 0.8

IMX is saved temporarily and it will be used in the next processing node.
Processing Function

In the case of buying processing node

\[ A_t \geq a_t (= 0.4) \Rightarrow \text{Buy} \]

In the case of selling processing node

\[ A_t \leq a_t (= 0.4) \Rightarrow \text{Sell} \]

\[ A_t \geq a_t (= 0.4) \Rightarrow \text{Take no action} \]
Judgment Function 2 - Candlestick Chart

- **Judgment Node** - Candlestick Chart

![Diagram of Candlestick Chart]

- **White Candlestick**
  - Upper Shadow
  - Close
  - Low

- **Black Candlestick**
  - Lower Shadow
  - Open
  - Close
  - High
Judgment Function 2 - Candlestick Chart

- Judge whether or not there is a window between yesterday’s price and the day before yesterday’s price.

- Judge whether or not yesterday’s closing price is higher than the day before yesterday’s opening price.
Flowchart

1. **Start**
2. Initialize all the individuals
3. **ind** ← 1
4. Trading (training) Sarsa
5. **Trail ends?**
   - **Yes**: Trading (testing)
   - **No**: **ind** ← **ind** + 1
6. **ind** = the number of individuals?
   - **Yes**: last generation?
   - **No**: reproduction
    - crossover
    - mutation

7. **last generation?**
   - **Yes**: stop
   - **No**: Trading (testing)
Learning Phase

- \( Q(s_t, a_t) \) is updated as follows:

\[
Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha [r_t + \gamma Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)]
\]

\( Q(s_t, a_t) \): State Value Function

- Reward \( r_t \) for action \( a_1 \)

- Action \( a_1 \), \( Q(s_t, a_1) = 2.0 \)

- Action \( a_2 \), \( Q(s_t, a_2) = 1.0 \)

State \( s_t \)

State \( s_{t+1} \)
Evolution Phase (Crossover)

1. Two individuals are selected as parents.
2. Each node is selected with the probability of $P_c$ and its genes (content and connections) are exchanged.
Evolution Phase (Mutation)

- Change connection
- Change node parameter

Change each connection with the probability of $P_m$

Change each parameter randomly with the probability of $P_m$

$a_{i1}=5$

$a_{i1}=10$
Simulation

Training: January 4, 2001-December 30, 2003 (737 days)
Testing: January 5, 2004-December 30, 2004 (246 days)

Reward = selling price - purchase price
Fitness = \sum Reward
Simulation

- Calculation periods of the technical index [day]

<table>
<thead>
<tr>
<th>Technical index</th>
<th>Period 1</th>
<th>Period 2</th>
<th>Period 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>ROD</td>
<td>5</td>
<td>13</td>
<td>26</td>
</tr>
<tr>
<td>RSI</td>
<td>5</td>
<td>13</td>
<td>26</td>
</tr>
<tr>
<td>ROC</td>
<td>5</td>
<td>13</td>
<td>26</td>
</tr>
<tr>
<td>VR</td>
<td>5</td>
<td>13</td>
<td>26</td>
</tr>
<tr>
<td>RCI</td>
<td>9</td>
<td>18</td>
<td>27</td>
</tr>
<tr>
<td>Stochastics</td>
<td>12</td>
<td>20</td>
<td>30</td>
</tr>
<tr>
<td>G/D Cross</td>
<td>5 (short)</td>
<td>26 (long)</td>
<td></td>
</tr>
<tr>
<td>MACD</td>
<td>5 (short)</td>
<td>26 (long)</td>
<td>9 (signal)</td>
</tr>
</tbody>
</table>
Simulation

- Simulation conditions

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of individuals</td>
<td>300</td>
</tr>
<tr>
<td>Mutation</td>
<td>179</td>
</tr>
<tr>
<td>Crossover</td>
<td>120</td>
</tr>
<tr>
<td>Elite</td>
<td>1</td>
</tr>
<tr>
<td>Number of nodes</td>
<td></td>
</tr>
<tr>
<td>Judgment node</td>
<td>31</td>
</tr>
<tr>
<td>Processing node</td>
<td>20</td>
</tr>
<tr>
<td>Start node</td>
<td>10</td>
</tr>
<tr>
<td>Number of sub-node</td>
<td>1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pc</td>
<td>0.1</td>
</tr>
<tr>
<td>Pm</td>
<td>0.02</td>
</tr>
<tr>
<td>α</td>
<td>0.1</td>
</tr>
<tr>
<td>γ</td>
<td>0.4</td>
</tr>
<tr>
<td>ε</td>
<td>0.1</td>
</tr>
</tbody>
</table>
Simulation Results in the Testing Simulations

<table>
<thead>
<tr>
<th>Brand</th>
<th>GNP-Sarsa</th>
<th>GNP</th>
<th>Buy&amp;Hold</th>
</tr>
</thead>
<tbody>
<tr>
<td>Toyota motor</td>
<td>522,333 (10.4)</td>
<td>480,500 (9.6)</td>
<td>520,000 (10.4)</td>
</tr>
<tr>
<td>Mitsubishi Estate</td>
<td>444,733 (8.9)</td>
<td>405,700 (8.1)</td>
<td>664,000 (13.3)</td>
</tr>
<tr>
<td>Showa Sell Sekiyu</td>
<td>263,100 (5.3)</td>
<td>294,755 (5.9)</td>
<td>319,200 (6.4)</td>
</tr>
<tr>
<td>East Japan Railway</td>
<td>413,833 (8.3)</td>
<td>491,500 (9.8)</td>
<td>477,000 (9.5)</td>
</tr>
<tr>
<td>NEC Corporation</td>
<td>36,600 (0.7)</td>
<td>-126,150 (-2.5)</td>
<td>-1,026,000 (-20.5)</td>
</tr>
<tr>
<td>Fuji Heavy Ind.</td>
<td>217,133 (4.3)</td>
<td>97,700 (2.0)</td>
<td>-189,000 (-3.8)</td>
</tr>
<tr>
<td>Sekisui House, Ltd.</td>
<td>582,466 (11.6)</td>
<td>54,600 (1.1)</td>
<td>264,000 (5.3)</td>
</tr>
<tr>
<td>Mitsu &amp; Co.</td>
<td>473,033 (9.5)</td>
<td>118,450 (2.4)</td>
<td>240,000 (4.8)</td>
</tr>
<tr>
<td>Sony</td>
<td>148,733 (3.0)</td>
<td>280,500 (5.6)</td>
<td>150,000 (3.0)</td>
</tr>
<tr>
<td>Tokyo Gas</td>
<td>669,733 (13.4)</td>
<td>382,000 (7.6)</td>
<td>372,000 (7.4)</td>
</tr>
<tr>
<td>KDDI</td>
<td>199,400 (4.0)</td>
<td>-76,600 (-1.5)</td>
<td>-576,000 (-11.5)</td>
</tr>
<tr>
<td>Tokyo Electric Power</td>
<td>570,266 (11.4)</td>
<td>210,000 (4.2)</td>
<td>262,500 (5.3)</td>
</tr>
<tr>
<td>Daiwa House</td>
<td>612,633 (12.3)</td>
<td>235,400 (4.7)</td>
<td>32,000 (0.6)</td>
</tr>
<tr>
<td>Nomura Holdings</td>
<td>366,033 (7.3)</td>
<td>-293,785 (5.9)</td>
<td>-985,500 (-19.7)</td>
</tr>
<tr>
<td>Shin-Etsu Chemical</td>
<td>562,700 (11.3)</td>
<td>7,250 (0.1)</td>
<td>-264,000 (-5.3)</td>
</tr>
<tr>
<td>Nippon Steel</td>
<td>469,866 (9.4)</td>
<td>-27,350 (0.5)</td>
<td>399,000 (8.0)</td>
</tr>
<tr>
<td>Average</td>
<td>409,537 (8.2)</td>
<td>158,404 (3.2)</td>
<td>41,200 (0.8)</td>
</tr>
</tbody>
</table>
Simulation

- **Fitness curve in the training period (Toyota Motor)**

![Graph showing the fitness curve in the training period](image-url)
Simulation

- Stock price of Toyota Motor and typical buying and selling point in 2004 (testing period)
Simulation

- Change of funds in the test simulation (Toyota Motor)
Simulation

- **Ratio of nodes used by GNP-Sarsa in the testing period (Toyota Motor)**
Chapter 2: A Portfolio Optimization Model using Genetic Network Programming with Control Nodes

- **Portfolio optimization** in the stock market consists of deciding what brands to include in a portfolio given the investor’s objectives and economic conditions.

- The main problem in our research is how to **allocate the available capital** to fixed stock brands in order to **maximize the profit**.

![Diagram showing allocation of capital to stocks](Image)
Basic Structure of GNP-cn

control nodes for brand $a$

control nodes for brand $b$

control nodes for brand $c$
Portfolio Optimization Algorithm

Training

1st
Initial (t, b, 1) = Initial (t) / |B|
Profit (t, b, 1) Profits (t, b, 1)
Profitability (t, b, 1) Profitability (t, b, 1)

nth
Initial (t, b, n)
Profit (t, b, n) Profits (t, b, n)
Profitability (t, b, n) Profitability (t, b, n)

(n+1)th
Initial (t, b, n+1)
Profit (t, b, n+1) Profits (t, b, n+1)
Profitability (t, b, n+1) Profitability (t, b, n+1)

Nth
Initial (t, b, N)
Profit (t, b, N) Profits (t, b, N)
Profitability (t, b, N) Profitability (t, b, N)

Testing
Initial (v, b)
Simulation

- **Parameter Conditions for Evolving GNPcn**

<table>
<thead>
<tr>
<th>Number of individual=300</th>
<th>(mutation:179, crossover:120, elite:1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of nodes=80</td>
<td>(Judgment node=20, Processing node=10, Control node=50)</td>
</tr>
<tr>
<td>Number of sub-node in each node=2</td>
<td></td>
</tr>
<tr>
<td>( P_c = 0.1, P_m = 0.03, \alpha = 0.1, \gamma = 0.3, \varepsilon = 0.1 )</td>
<td></td>
</tr>
</tbody>
</table>

- **Average Fitness Values [million yen] in Training Period with Different \( T \)**

<table>
<thead>
<tr>
<th>( T )</th>
<th>0.001</th>
<th>0.003</th>
<th>0.005</th>
<th>0.01</th>
<th>0.03</th>
<th>0.05</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fitness</td>
<td>133.5</td>
<td>143.2</td>
<td>136.2</td>
<td>125.6</td>
<td>110.1</td>
<td>108.2</td>
</tr>
</tbody>
</table>
Simulation

- Fitness and profit curves of 10 brands in the training period
Simulation

- Profits change of 10 brands in the testing period
Simulation

- Profits in the testing simulations {Profit [yen] (profitability [%])}

<table>
<thead>
<tr>
<th>Brand</th>
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<th>GNP-CS</th>
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<th>Buy&amp;Hold</th>
</tr>
</thead>
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<td>NEC Corporation</td>
<td>---</td>
<td>43,400 (0.9)</td>
<td>-126,150 (-2.5)</td>
<td>-531,000 (-10.6)</td>
<td>-1,026,000 (-20.5)</td>
</tr>
<tr>
<td>Fuji Heavy Ind.</td>
<td>---</td>
<td>188,800 (3.8)</td>
<td>97,700 (2.0)</td>
<td>173,000 (3.5)</td>
<td>-189,000 (-3.8)</td>
</tr>
<tr>
<td>East Japan Railway</td>
<td>---</td>
<td>418,800 (8.4)</td>
<td>96,550 (1.9)</td>
<td>7,590 (0.2)</td>
<td>477,000 (9.5)</td>
</tr>
<tr>
<td>KDDI</td>
<td>---</td>
<td>316,233 (6.3)</td>
<td>-76,600 (-1.5)</td>
<td>-273,000 (-5.5)</td>
<td>-576,000 (-11.5)</td>
</tr>
<tr>
<td>Nomura Holding, Inc.</td>
<td>---</td>
<td>638,933 (12.8)</td>
<td>-293,785 (-5.9)</td>
<td>-374,087 (-7.5)</td>
<td>-985,500 (-19.7)</td>
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<td>Shin-Etsu Chemical</td>
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<td>133,800 (2.7)</td>
<td>7,250 (0.1)</td>
<td>-539,400 (-10.8)</td>
<td>-264,000 (-5.3)</td>
</tr>
<tr>
<td>Sony</td>
<td>---</td>
<td>202,766 (4.1)</td>
<td>280,500 (5.6)</td>
<td>112,000 (2.2)</td>
<td>150,000 (3.0)</td>
</tr>
<tr>
<td>Tokyo Electric Power</td>
<td>---</td>
<td>116,100 (2.3)</td>
<td>-69,500 (-1.3)</td>
<td>360,750 (7.2)</td>
<td>262,500 (5.3)</td>
</tr>
<tr>
<td>Hitachi</td>
<td>---</td>
<td>403,366 (8.1)</td>
<td>472,300 (9.4)</td>
<td>276,300 (5.5)</td>
<td>336,000 (6.7)</td>
</tr>
<tr>
<td>Nissan</td>
<td>---</td>
<td>464,966 (9.3)</td>
<td>590,750 (11.8)</td>
<td>372,000 (7.4)</td>
<td>450,000 (9.0)</td>
</tr>
<tr>
<td>Average</td>
<td>4,262,714 (8.5)</td>
<td>292,716 (5.9)</td>
<td>98,302 (2.0)</td>
<td>-41,585 (-0.8)</td>
<td>-136,500 (-2.7)</td>
</tr>
</tbody>
</table>
Thank you for your attention!

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