Evolutionary Multi-Objective Optimisation for Men’s Elite Level Track Cycling – A Real World Cooperative Hierarchical Optimisation Problem

By Claire Diora Jordan
School of Computer Science
University of Adelaide, Australia

With support from Dr David Martin from the Australian Institute of Sport and Dr Tammie Ebert from Cycling Australia
Intro

• **Aim**: To model and optimize strategies for Men’s Team Pursuit Cycling Event.

• Problem is difficult as it involves *multi-objective hierarchical solutions* spread over a multimodal solution space.

• Significant as it links between EC theory *and real world problems*. 
Men’s Team Pursuit Track Cycling

- 4 riders around a velodrome.
- Lead rider exerts more energy while following riders get the benefit of slip streaming.
- To expend maximum energy lead rider changes – this is the transition strategy.
- Each rider uses an amount of power on each half lap – this is the pacing strategy.
- Only 3 of the 4 riders are required to finish – adds complexity to the problem.
Problem Formulation

- Have **2 core parameters** that make up the strategy:
- **Transition Strategy** – The number of half laps before transitioning - discrete
- **Pacing Strategy** – The power output of the front rider per half lap – continuous

<table>
<thead>
<tr>
<th>HL₁</th>
<th>HL₂</th>
<th>...</th>
<th>HLₘ</th>
</tr>
</thead>
<tbody>
<tr>
<td>P₁</td>
<td>P₂</td>
<td>...</td>
<td>Pₙ</td>
</tr>
</tbody>
</table>
Fitness Function

• Aim is to **minimize the time** of a race.
• Use a forward integration technique to simulate the time and energy used by the first rider to ride a half lap.

\[ \Delta KE = (P \times E - C_D A \times \left( \frac{1}{2} \rho v^3 \right) - \mu \times (vF_N)) \times \Delta t \]

• Find power taken for following riders to keep up with the first rider.

\[ P = (C_D A \times C_{Draft} \times \frac{1}{2} \rho v^3 + \mu \times (vF_N) + \frac{\Delta KE}{\Delta t}) / E \]

• **Penalty function** if 2 or more riders run out of energy.
Multi-Objective

• Aim of optimization:
  • Minimize the race time
  • Maximize the remaining energy

• Limited research has been done in the area of hierarchical multi-objective optimization problems – both in theoretical and practical domain
Operators

• 2 halves of the problem that require different types of operators.

• Discrete Transition Strategy
  • Random mutation
  • Creep mutation

• Continuous pacing Strategy
  • Uniform mutation
  • Non-uniform mutation

• Note: Due to the nature of the problem crossover makes no sense, so is not used.
Basic Approach – Single Level

- **Non problem specific technique** – it does not take into account the hierarchical nature of the problem.
- Mutates solution as **one large problem**.

| HL₁ | HL₂ | ... | HLₘ | P₁ | P₂ | ... | Pₙ |
Nested Algorithm

- Problem has **2 levels:**
  - Leader – the transition strategy
  - Follower – the pacing strategy
- Create **separate EAs** for the leader and follower problem
- For each new solution to the leader problem optimise the follower problem.
- Combine the results of both EAs to get the parents for the next generation of the leader EA.
Nested Algorithm

• Algorithms used for Leader and Follower:
  • NSGAII – established algorithm
  • SPEAII – established algorithm
  • MO-CMA-ES – established algorithm

• Found these explored too big a time range so introduced:
  • Greedy – given a set of $\lambda$ solutions, selects $\mu$ solutions with fastest race times
  • Greedy+Random - given a set of $\lambda$ solutions, selects $\mu/2$ solutions with fastest race times and $\mu/2$ solutions randomly.
Experimental Design

• Found the best combination of operators using the single level optimisation for each algorithm
• To compare algorithms a fixed number of evaluations was used – 2 million as it takes approx. 3 hours.
• Created a realistic model of the race parameters given to us by the Australian Institute of Sport.
# Results

## SPEAII-SPEAII

<table>
<thead>
<tr>
<th>Time</th>
<th>Energy</th>
</tr>
</thead>
<tbody>
<tr>
<td>251.76</td>
<td>3482</td>
</tr>
<tr>
<td>260.84</td>
<td>27749</td>
</tr>
<tr>
<td>270.82</td>
<td>56294</td>
</tr>
<tr>
<td>280.14</td>
<td>74175</td>
</tr>
<tr>
<td>295.74</td>
<td>96226</td>
</tr>
<tr>
<td>312.84</td>
<td>123248</td>
</tr>
<tr>
<td>323.34</td>
<td>143810</td>
</tr>
<tr>
<td>334.52</td>
<td>161780</td>
</tr>
<tr>
<td>363.64</td>
<td>192034</td>
</tr>
<tr>
<td>384.66</td>
<td>207959</td>
</tr>
</tbody>
</table>

## Greedy+Random-SPEAII

<table>
<thead>
<tr>
<th>Time</th>
<th>Energy</th>
</tr>
</thead>
<tbody>
<tr>
<td>247.36</td>
<td>1188</td>
</tr>
<tr>
<td>247.37</td>
<td>2573</td>
</tr>
<tr>
<td>247.96</td>
<td>3106</td>
</tr>
<tr>
<td>248.36</td>
<td>5406</td>
</tr>
<tr>
<td>265.06</td>
<td>35741</td>
</tr>
<tr>
<td>278.76</td>
<td>64414</td>
</tr>
<tr>
<td>312.00</td>
<td>122626</td>
</tr>
<tr>
<td>315.30</td>
<td>126218</td>
</tr>
<tr>
<td>335.70</td>
<td>161812</td>
</tr>
</tbody>
</table>
Analysis

- Preliminary results show nested approach better than standard approach.
- Worse time results than single objective approach - Increased diversity of multi-objective approach gives too much emphasis to remaining energy
- Need to further explore weightings for the objectives
Conclusion

• Developed and applied generalised algorithms to a real life problem
• Simplest of algorithms still outperformed unoptimised solution.
• Preliminary results show nested approach better than standard approach.
• Increased diversity of multi-objective approach appears to be worse than single objective approach.
• Generalised algorithms proved sufficient for our domain and can be applied to other real world problems in the future.
Future Work

- Explore weighting the objective values
- Development of more efficient algorithms
  - co-evolutionary algorithm
  - effect of inner algorithm
- Calibrate results with real cyclists.
- Application to other real life problems.
Questions?