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

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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

HL_1	HL_2	...	HL_m
P_1	P_2	...	P_n

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.

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

- 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.

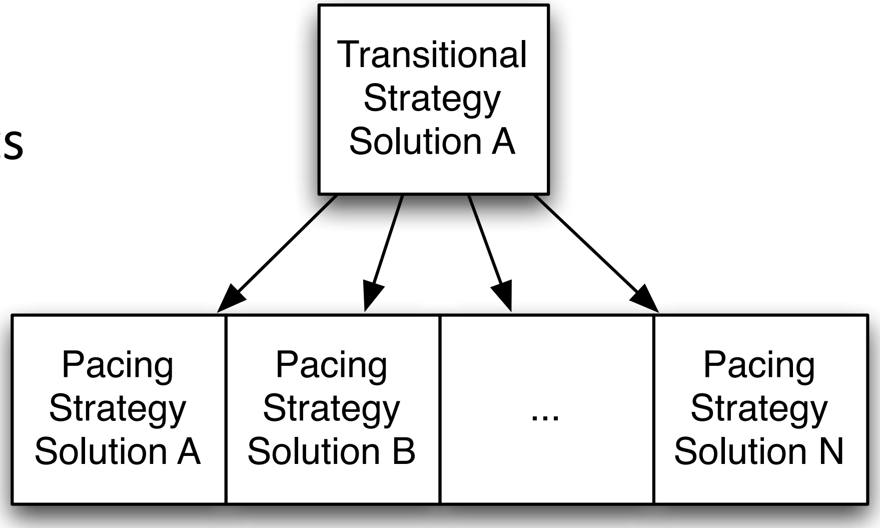
Basic Approach – Single Level

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

HL_1	HL_2	...	HL_m	P_1	P_2	...	P_n

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 λ solutions, selects μ solutions with fastest race times
  - Greedy+Random - given a set of λ 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

Time	Energy
251.76	3482
260.84	27749
270.82	56294
280.14	74175
295.74	96226
312.84	123248
323.34	143810
334.52	161780
363.64	192034
384.66	207959

Greedy+Random-SPEAII

Time	Energy
247.36	1188
247.37	2573
247.96	3106
248.36	5406
265.06	35741
278.76	64414
312.00	122626
315.30	126218
335.70	161812

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?