Evolutionary Computation for Dynamic Optimization Problems

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Presenter — Shengxiang Yang

- Education and career history:
  - PhD, Northeastern University, China, 1999
  - Worked at King's College London, University of Leicester, and Brunel University, 1999-2012
  - Joined De Montfort University (DMU) as Professor in Computational Intelligence (CI) in July 2012
  - Director of Centre for Computational Intelligence (CCI)
- Research interests:
  - Evolutionary Computation (EC) and nature-inspired computation
  - Dynamic optimisation and multi-objective optimisation
  - Relevant real-world applications
- Over 230 publications and £2M funding for research
- AE/Editorial Board Member for 8 journals, including *IEEE Trans Cybern*, *Evol Comput*, *Inform Sci*, *Neurocomputing*, and *Soft Comput*
- Chair of two IEEE CIS Task Forces
  - EC in Dynamic and Uncertain Environments
  - Intelligent Network Systems

Centre for Computational Intelligence (CCI)

- CCI (www.cci.dmu.ac.uk):
  - Mission: Developing fundamental theoretical and practical solutions to real-world problems using a variety of CI paradigms
  - Members: 18 staff, several research fellows, 30+ PhDs, visiting researchers
  - Themes: EC, fuzzy logic, neural networks, data mining, robotics, game ...
- Funding:
  - Research Councils/Charities: EPSRC, ESRC, EU FP7 & Horizon 2020, Royal Academy of Engineering, Royal Society, Innovate UK, KTP, Innovation Fellowships, Nuffield Trust, etc.
  - Government: Leicester City Council, DTI
  - Industries: Lachesis, EMDA, RSSB, Network Rail, etc.
- Collaborations:
  - Universities: UK, USA, Spain, and China
  - Industries and local governments
- Teaching/Training:
  - DTP-IS: University Doctor Training Programme in Intelligent Systems
  - MSc Intelligent Systems, MSc Intelligent Systems & Robotics
  - BSc Artificial Intelligence with Robotics
- YouTube page: http://www.youtube.com/thecci

Outline of the Tutorial

Part I: Fundamentals

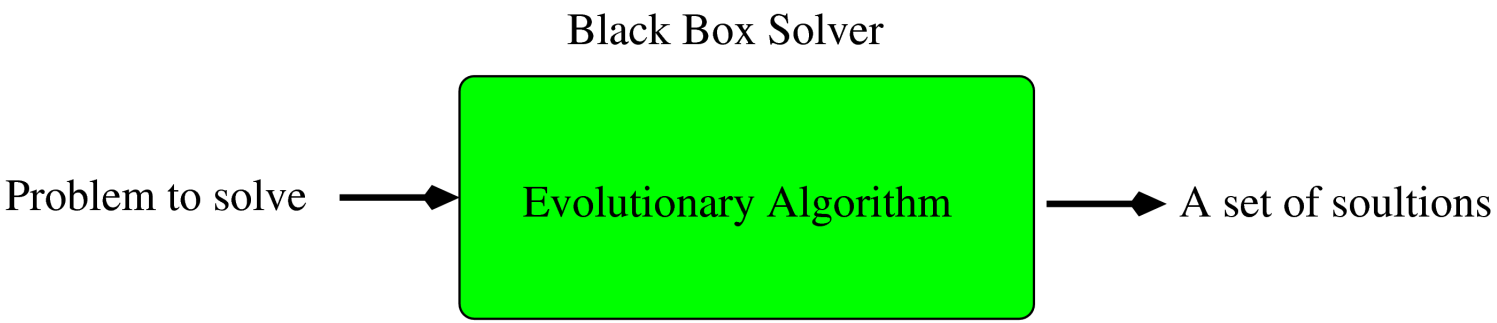
- Introduction to evolutionary computation (EC)
- EC for dynamic optimization problems (DOPs): Concept and motivation
- Benchmark and test problems
- Performance measures

Part II: Approaches, Issues and Future Work

- EC enhancement approaches for DOPs
- Case studies
- Relevant issues
- Future work

What Is Evolutionary Computation (EC)?

- EC encapsulates a class of stochastic optimization algorithms, dubbed Evolutionary Algorithms (EAs)
- An EA is an optimisation algorithm that is
  - Generic: a black-box tool for many problems
  - Population-based: evolves a population of candidate solutions
  - Stochastic: uses probabilistic rules
  - Bio-inspired: uses principles inspired from biological evolution



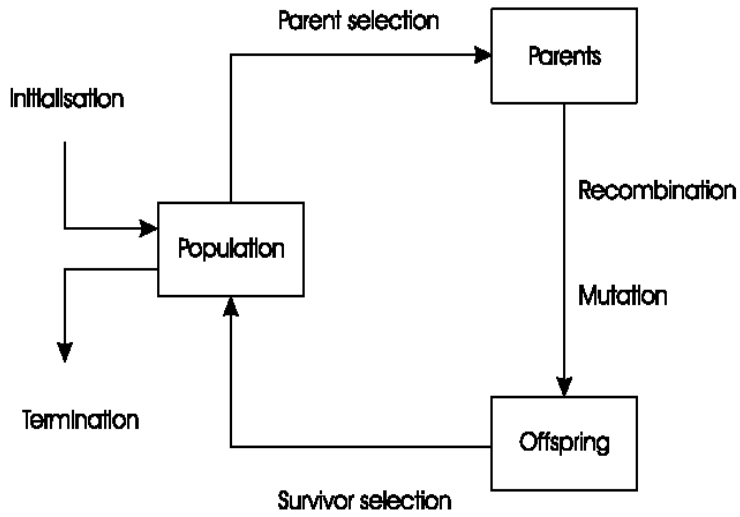
Design and Framework of an EA

Given a problem to solve, first consider two key things:

- Representation of solution into individual
- Evaluation or fitness function

Then, design the framework of an EA:

- Initialization of population
- Evolve the population
  - Selection of parents
  - Variation operators (recombination & mutation)
  - Selection of offspring into next generation
- Termination condition: a given number of generations

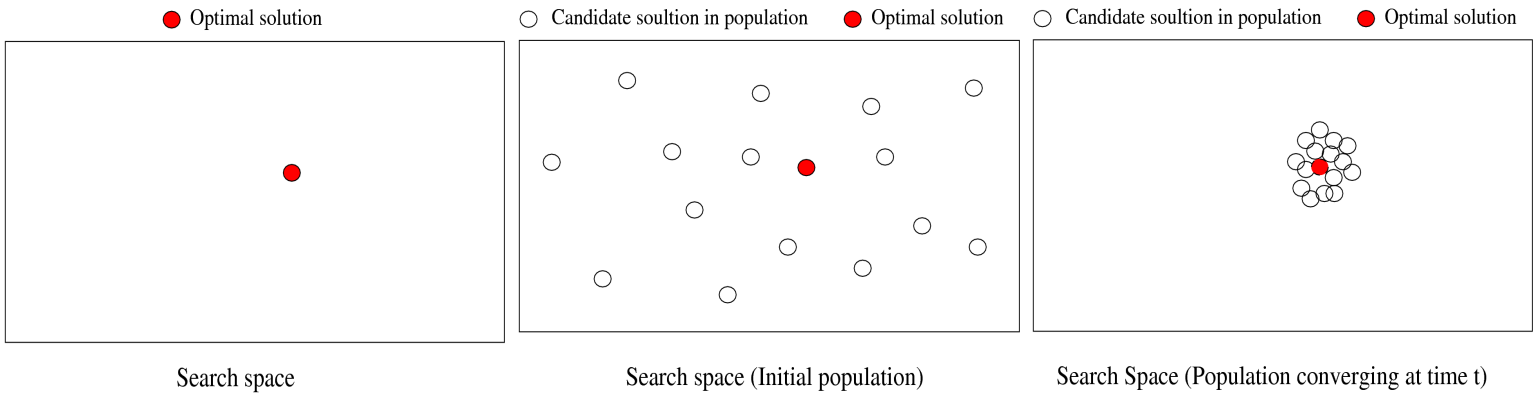


EC Applications

- EAs are easy-to-use: No strict requirements to problems
- Widely used for optimisation and search problems
  - Financial and economical systems
  - Transportation and logistics systems
  - Industry engineering
  - Automatic programming, art and music design
  - .....

EC for Optimisation Problems

- Traditionally, research on EAs has focused on static problems
  - Aim to find the optimum *quickly* and *precisely*



- But, many real-world problems are dynamic optimization problems (DOPs), where changes occur over time
  - In transport networks, travel time between nodes may change
  - In logistics, customer demands may change

What Are DOPs?

- In general terms, “optimization problems that change over time” are called *dynamic problems/time-dependent problems*

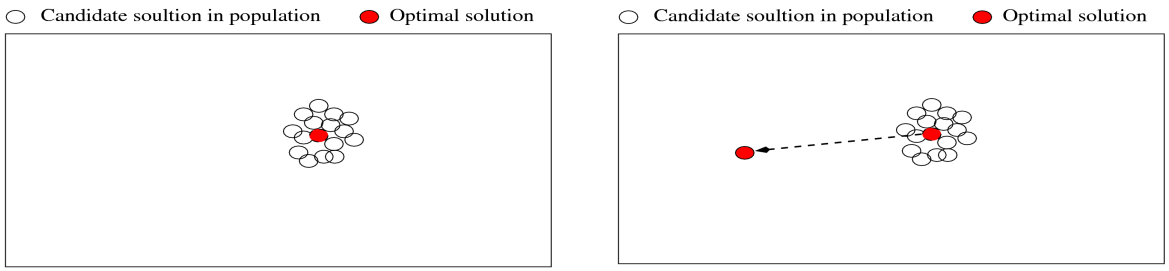
$$F = f(\vec{x}, \vec{\phi}, t)$$

  – $\vec{x}$: decision variable(s); $\vec{\phi}$: parameter(s); t: time

- DOPs: special class of dynamic problems that are solved online by an algorithm as time goes by

Why DOPs Challenge EC?

- For DOPs, optima may move over time in the search space
  - Challenge: need to track the moving optima over time



- DOPs challenge traditional EAs
  - Once converged, hard to escape from an old optimum

Why EC for DOPs?

- Many real-world problems are DOPs
- EAs, once properly enhanced, are good choice
  - Inspired by natural/biological evolution, always in dynamic environments
  - Intrinsically, should be fine to deal with DOPs
- Many events on EC for DOPs recently

Relevant Events

- Books (Monograph or Edited):
  - Yang & Yao, 2013; Alba *et al.*, 2013; Yang *et al.*, 2007; Morrison, 2004; Weicker, 2003; Branke, 2002
- PhD Theses:
  - Jiang, 2017; Mavrovouniotis, 2013; Helbig, 2012; du Plessis, 2012; Li, 2011; Nguyen, 2011; Simoes, 2010
- Journal special issues:
  - Neri & Yang, 2010; Yang *et al.*, 2006; Jin & Branke, 2006; Branke, 2005
- Workshops and conference special sessions:
  - EvoSTOC (2004–2017): part of Evo*
  - ECiDUE (2004–2017): part of IEEE CEC
  - EvoDOP (’99, ’01, ’03, ’05, ’07, ’09): part of GECCO
- IEEE Symposium on CIDUE (2011, 2013-2017)
- IEEE Competitions: within IEEE CEC’09, CEC’12 & CEC’14

Benchmark and Test DOPs

- Basic idea: change base static problem(s) to create DOPs
- Real space:
  - Switch between different functions
  - Move/reshape peaks in the fitness landscape
- Binary space:
  - Switch between $\geq$ 2 states of a problem: knapsack
  - Use binary masks: XOR DOP generator (Yang & Yao'05)
- Combinatorial space:
  - Change decision variables: item weights/profits in knapsack problems
  - Add/delete decision variables: new jobs in scheduling, nodes added/deleted in network routing problems

The DF1 Generator

- Proposed by Morrison & De Jong (1999)
- The base landscape in the D-dimensional real space:

$$f(\vec{x}) = \max_{i=1,\ldots,p} \left[H_i - R_i \times \sqrt{\sum_{j=1}^{D} (x_j - X_{ij})^2} \right]$$

  – $\vec{x} = (x_1, \cdots, x_D)$: a point in the landscape; p: number of peaks
  – H_i, R_i, $X_i = (X_{i1}, \cdots, X_{iD})$: height, slope, center of peak i

- The dynamics is controlled by a logistics function:

$$\Delta_t = A \cdot \Delta_{t-1} \cdot (1 - \Delta_{t-1})$$

  – $A \in [1.0, 4.0]$: a constant; Δ_t: step size of changing a parameter

Moving Peaks Benchmark (MPB) Problem

- Proposed by Branke (1999)
- The MPB problem in the D-dimensional space:

$$F(\vec{x}, t) = \max_{i=1,\ldots,p} \frac{H_i(t)}{1 + W_i(t) \sum_{j=1}^{D} (x_j(t) - X_{ij}(t))^2}$$

  – $W_i(t)$, $H_i(t)$, $X_i(t) = \{X_{i1} \cdots X_{iD}\}$: height, width, location of peak i at t

- The dynamics:

$$H_i(t) = H_i(t-1) + \mathit{height\_severity} * \sigma$$

$$W_i(t) = W_i(t-1) + \mathit{width\_severity} * \sigma$$

$$\vec{v}_i(t) = \frac{s}{\left|\vec{r} + \vec{v}_i(t-1)\right|}((1-\lambda)\vec{r} + \lambda\vec{v}_i(t-1))$$

$$\vec{X}_i(t) = \vec{X}_i(t)(t-1) + \vec{v}_i(t)$$

  – $\sigma \sim N(0,1)$; λ: correlated parameter

  – $\vec{v}_i(t)$: shift vector, which combines random vector $\vec{r}$ and $\vec{v}_i(t-1)$ and is normalized to the shift length s

Dynamic Knapsack Problems (DKPs)

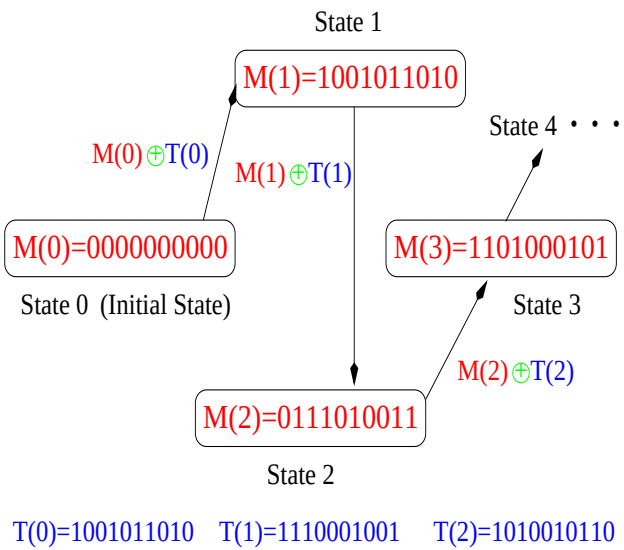
- Static knapsack problem:
  - Given n items, each with a weight and a profit, and a knapsack with a fixed capacity, select items to fill up the knapsack to maximize the profit while satisfying the knapsack capacity constraint
- The DKP:
  - Constructed by changing weights and profits of items, and/or knapsack capacity over time as:

$$Max\ f(\vec{x}(t),t) = \sum_{i=1}^{n} p_i(t) \cdot x_i(t), \quad s.t.: \quad \sum_{i=1}^{n} w_i(t) \cdot x_i(t) \leq C(t)$$

  - $\vec{x}(t) \in \{0,1\}^n$: a solution at time t
  - $x_i(t) \in \{0,1\}$: indicates whether item i is included or not
  - $p_i(t)$ and $w_i(t)$: profit and weight of item i at t
  - $C(t)$: knapsack capacity at t

The XOR DOP Generator

- The **XOR DOP generator** can create DOPs from any binary $f(\vec{x})$ by an XOR operator "$\oplus$" (Yang, 2003; Yang & Yao, 2005)
- Suppose the environment changes every τ generations
- For each environmental period $k = \lfloor t/\tau \rfloor$, do:



1. Create a template T_k with $\rho * l$ ones
2. Create a mask $\vec{M}(k)$ incrementally

$$\vec{M}(0) = \vec{0} \text{ (the initial state)}$$

$$\vec{M}(k+1) = \vec{M}(k) \oplus \vec{T}(k)$$

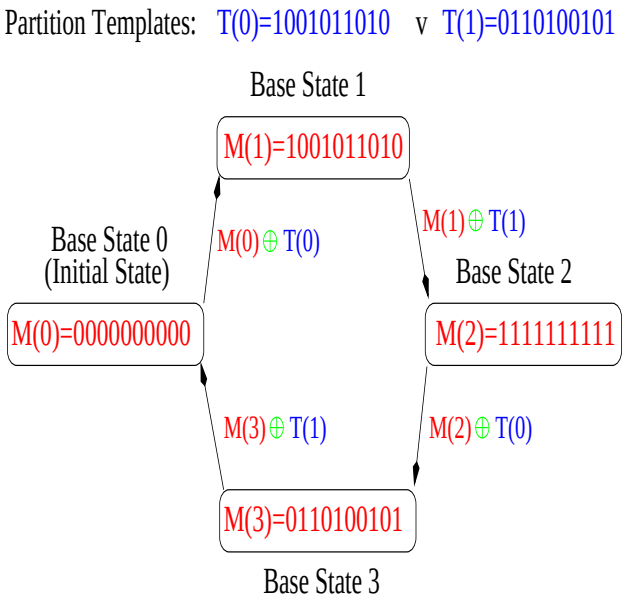
3. Evaluate an individual:

$$f(\vec{x}, t) = f(\vec{x} \oplus \vec{M}(k))$$

- τ and ρ controls the speed and severity of change respectively

Constructing Cyclic Dynamic Environments

Can extend the XOR DOP generator to create cyclic environments:



1. Construct K templates $\vec{T}(0),\cdots,\vec{T}(K-1)$
   - Form a partition of the search space
   - Each contains $\rho \times l = l/K$ ones
2. Create $2K$ masks $\vec{M}(i)$ as *base states*

$$\vec{M}(0) = \vec{0} \text{ (the initial state)}$$

$$\vec{M}(i+1) = \vec{M}(i) \oplus \vec{T}(i\%K), i = 0,\cdots,2K-1$$

3. Cycle among $\vec{M}(i)$'s every τ generations

$$f(\vec{x},t) = f(\vec{x} \oplus \vec{M}(l_t)) = f(\vec{x} \oplus \vec{M}(k\%(2K)))$$

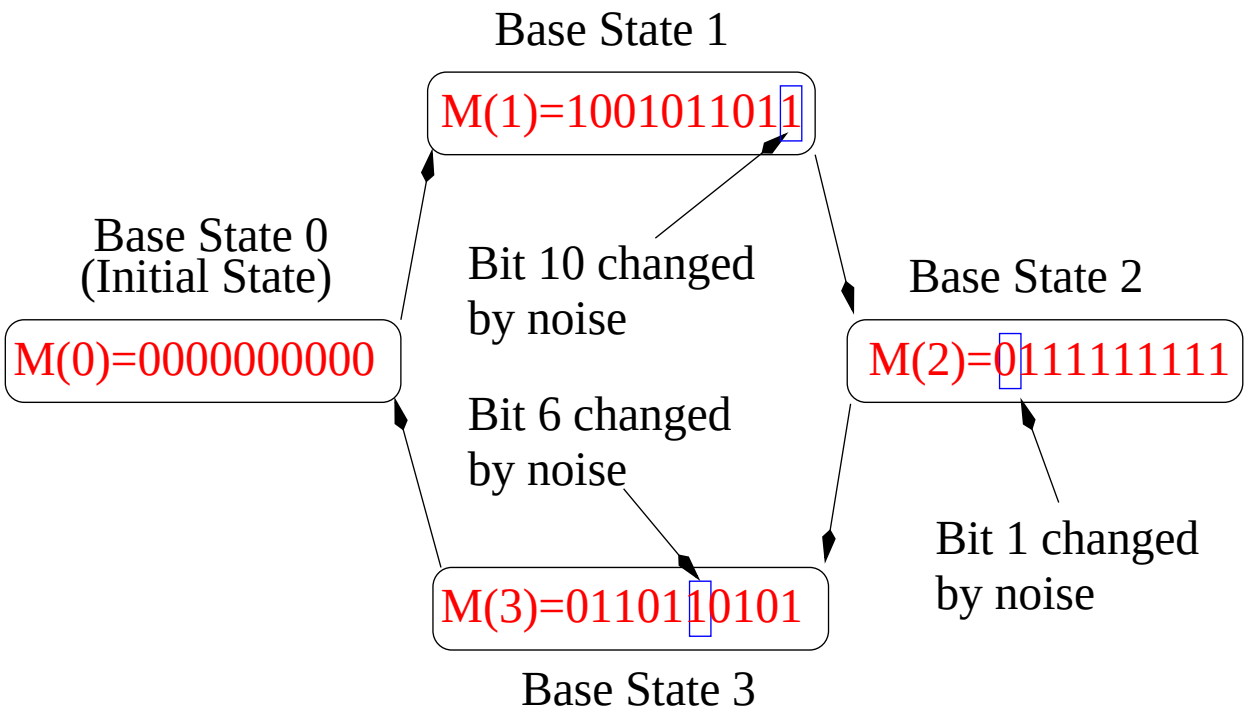
– $k = \lfloor t/\tau \rfloor$: environmental index

– $l_t = k\%(2K)$: mask index

Constructing Cyclic Environments with Noise

We can also construct cyclic environments with noise:

- Each time before a base state is entered, it is bitwise changed with a small probability



Dynamic Traveling Salesman Problems

- Stationary traveling salesman problem (TSP):
  - Given a set of cities, find the shortest route that visits each city once and only once
- Dynamic TSP (DTSP):
  - May involve dynamic cost (distance) matrix

$$D(t) = \{d_{ij}(t)\}_{n*n}$$

  – $d_{ij}(t)$: cost from city i to j; n: the number of cities
  - The aim is to find a minimum-cost route containing all cities at time t
  - DTSP can be defined as $f(x, t)$:

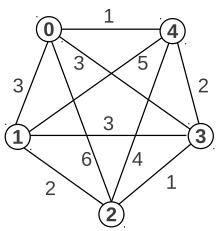
$$f(x, t) = Min(\sum_{i=1}^{n} d_{x_i, x_{i+1}}(t))$$

where $x_i \in 1, \cdots, n$. If $i \neq j$, $x_i \neq x_j$, and $x_{n+1} = x_1$

Dynamic Permutation Benchmark Generator

- The dynamic benchmark generator for permutation-encoded problems (DBGP) can create a DOP from any stationary TSP/VRP by swapping objects:

Optimum -> (0,4,3,2,1,0) = 9

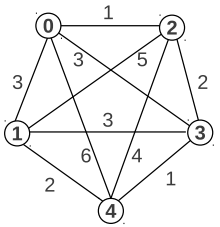


Distance matrix before change

	0	1	2	3	4
0	0	3	6	5	1
1	3	0	2	3	3
2	6	2	0	1	4
3	5	3	1	0	2
4	1	3	4	2	0

Swap City Location (4,2)

Optimum -> (0,2,3,4,1,0) = 9



Distance matrix after change

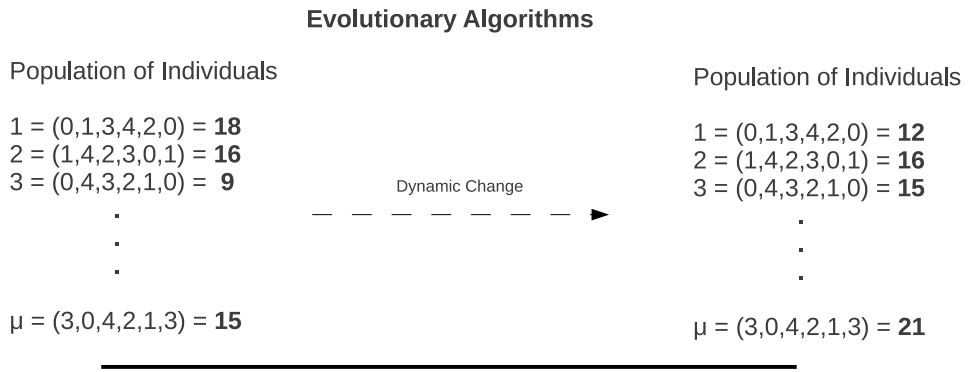
	0	1	2	3	4
0	0	3	1	5	6
1	3	0	3	3	2
2	1	3	0	2	4
3	5	3	2	0	1
4	6	2	4	1	0

1. Generate a random vector $\vec{r}(T)$ that contains all objects every f iterations
2. Generate another randomly re-order vector $\vec{r'}(T)$ that contains only the first $m \times n$ objects of $\vec{r}(T)$
3. Modify the encoding of the problem instance with $m \times n$ pairwise swaps

- More details: M. Mavrovouniotis, S. Yang, & X. Yao (2012). *PPSN XII*, Part II, LNCS 7492, pp. 508–517

Effect on Algorithms

- Similar with the XOR DOP generator, DBGP shifts the population of an alg. to new location in the fitness landscape
- The individual with the same encoding as before a change will have a different cost after the change



Ant Colony Optimization

Heuristic Information Matrix

	0	1	2	3	4
0	0	0.33	0.16	0.08	1
1	0.33	0	0.5	0.33	0.33
2	0.16	0.5	0	1	0.25
3	0.2	0.33	1	0	0.5
4	1	0.33	0.25	0.5	0

Dynamic Change

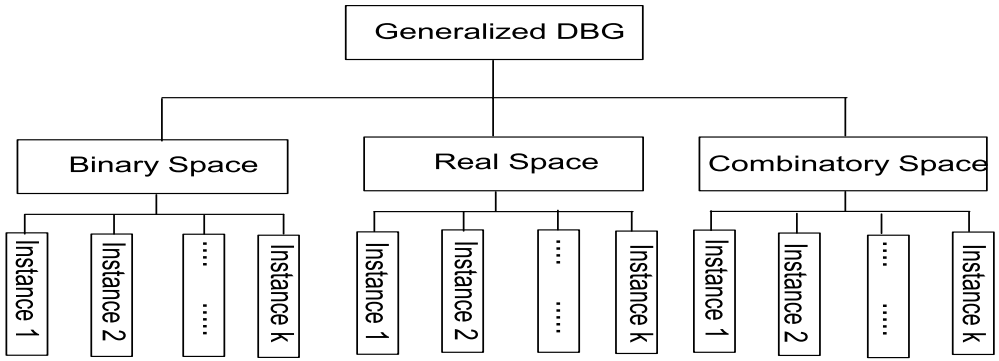
Heuristic Information Matrix

	0	1	2	3	4
0	0	0.33	1	0.2	0.16
1	0.33	0	0.33	0.33	0.5
2	1	0.33	0	0.5	0.25
3	0.2	0.33	0.5	0	1
4	0.16	0.5	0.25	1	0

- Can extend for cyclic and cyclic with noise environments

Generalized DOP Benchmark Generator (GDBG)

- Proposed by Li & Yang (2008), GDBG uses the model below:



- In GDBG, DOPs are defined as:

$$F = f(x, \phi, t),$$

  – ϕ: system control parameter
- Dynamism results from tuning ϕ of the current environment

$$\phi(t+1) = \phi(t) \oplus \Delta\phi$$

  – $\Delta\phi$: deviation from the current control parameter(s)
- The new environment at $t+1$ is as follows:

$$f(x, \phi, t+1) = f(x, \phi(t) \oplus \Delta\phi, t)$$

GDBG: Dynamic Change Types

- Change types:
  1. Small step: $\Delta\phi = \alpha \cdot \|\phi\| \cdot rand()$
  2. Large step: $\Delta\phi = \|\phi\| \cdot (\alpha + (1-\alpha) rand())$
  3. Random: $\Delta\phi = \|\phi\| \cdot rand()$
  4. Chaotic: $\phi(t+1) = A \cdot \phi(t) \cdot (1 - \phi(t)/\|\phi\|)$
  5. Recurrent: $\phi(t+1) = \phi(t\%P)$
  6. Recurrent with nosy: $\phi(t+1) = \phi(t\%P) + \alpha \cdot \|\phi\| \cdot rand()$
  7. .....
- More details:
  - C. Li & S. Yang (2008). *SEAL'08*, LNCS 5361, pp. 391–400

DOPs: Classification

Classification criteria:

- Time-linkage: Does the future behaviour of the problem depend on the current solution?
- Predictability: Are changes predictable?
- Visibility: Are changes visible or detectable
- Cyclicity: Are changes cyclic/recurrent in the search space?
- Factors that change: objective, domain/number of variables, constraints, and/or other parameters

DOPs: Common Characteristics

Common characteristics of DOPs in the literature:

- Most DOPs are non time-linkage problems
- For most DOPs, changes are assumed to be detectable
- In most cases, the objective function is changed
- Many DOPs have unpredictable changes
- Most DOPs have cyclic/recurrent changes

Performance Measures

- For EC for stationary problems, 2 key performance measures
  - Convergence speed
  - Success rate of reaching optimality
- For EC for DOPs, over 20 measures (Nguyen et al., 2012)
  - Optimality-based performance measures
    - Collective mean fitness or mean best-of-generation
    - Accuracy
    - Adaptation
    - Offline error and offline performance
    - Mean distance to optimum at each generation
    - .....
  - Behaviour-based performance measures
    - Reactivity
    - Stability
    - Robustness
    - Satisficability
    - Diversity measures
    - .....

Performance Measures: Examples

- Collective mean fitness (mean best-of-generation):

$$\overline{F}_{BOG} = \frac{1}{G} \times \sum_{i=1}^{i=G} (\frac{1}{N} \times \sum_{j=1}^{j=N} F_{BOG_{ij}})$$

  – G and N: number of generations and runs, resp.

  – $F_{BOG_{ij}}$: best-of-generation fitness of generation i of run j

- Adaptation performance (Mori et al., 1997)

$$Ada = \frac{1}{T} \sum_{t=1..T} (f_{best}(t)/f_{opt}(t))$$

- Accuracy (Trojanowski and Michalewicz, 1999)

$$Acc = \frac{1}{K} \sum_{i=1..K} (f_{best}(i) - f_{opt}(i))$$

  – $f_{best}(i)$: best fitness for environment i (best before change)

Part II: Approaches, Issues and Future Work

- EC enhancement approaches for DOPs
- Case studies
- Relevant issues
- Future work

EC for DOPs: First Thinking

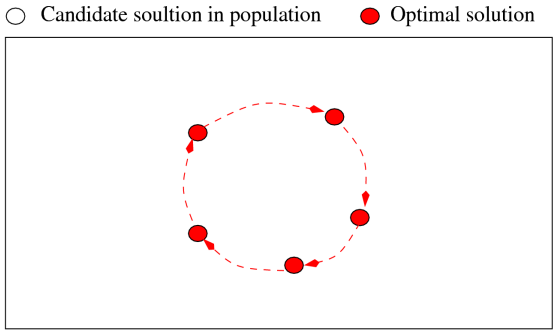
- Recap: traditional EAs are not good for DOPs
- Goal: to track the changing optimum
- How about restarting an EA after a change?
  - Natural and easy choice
  - But, not good choice because:
    1. It may be inefficient, wasting computational resources
    2. It may lead to very different solutions before and after a change.
       For real-world problems, we may expect solutions to remain similar
- Extra approaches are needed to enhance EAs for DOPs

EC for DOPs: General Approaches

- Many approaches developed to enhance EAs for DOPs
- Typical approaches:
  - Memory: store and reuse useful information
  - Diversity: handle convergence directly
  - Multi-population: co-operate sub-populations
  - Adaptive: adapt generators and parameters
  - Prediction: predict changes and take actions in advance
- They have been applied to different EAs for DOPs

Memory Approaches

- Cyclic DOPs: change cyclically among a fixed set of states

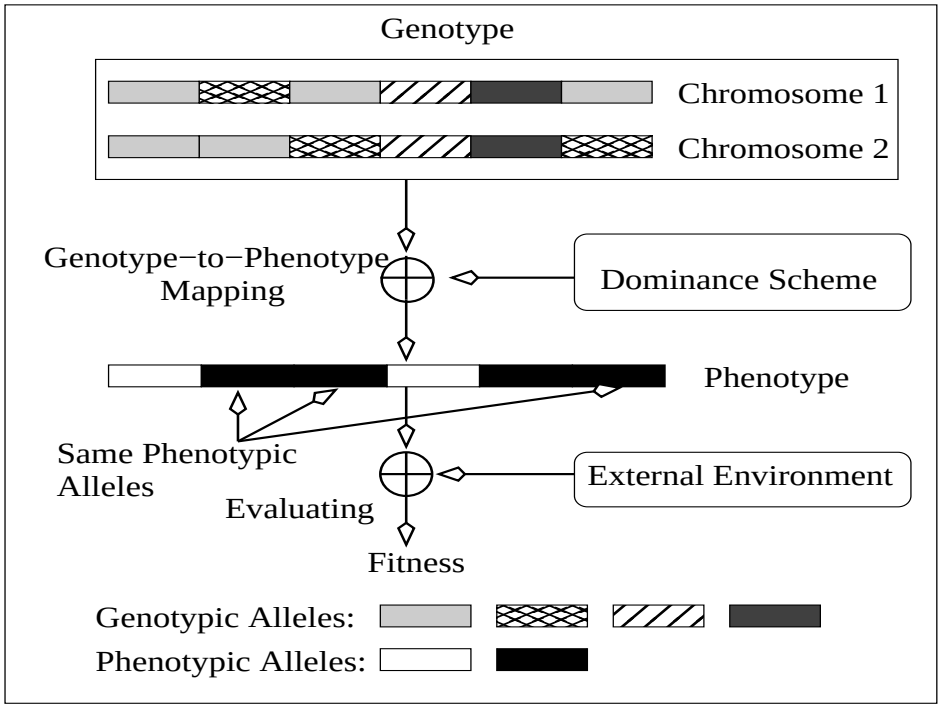


Search space (Optimum moves cyclically)

- Memory works by storing and reusing useful information
- Two classes regarding how to store information
  - Implicit memory: uses redundant representations
    - Multiploidy and dominance (Ng & Wong, 1995; Lewis et al., 1998)
    - Dualism mechanisms (Yang, 2003; Yang & Yao, 2005)
  - Explicit memory: uses extra space to store information

Implicit Memory: Diploid Genetic Algorithms

Encoding



Dominance Scheme

	0	o	1	i
0	0	0	0/1	0
o	0	0	1	0/1
1	0/1	1	1	1
i	0	0/1	1	1

Ng & Wong (1995)

	A	B	C	D
A	0	0	0	1
B	0	0	0	1
C	0	0	1	1
D	1	1	1	1

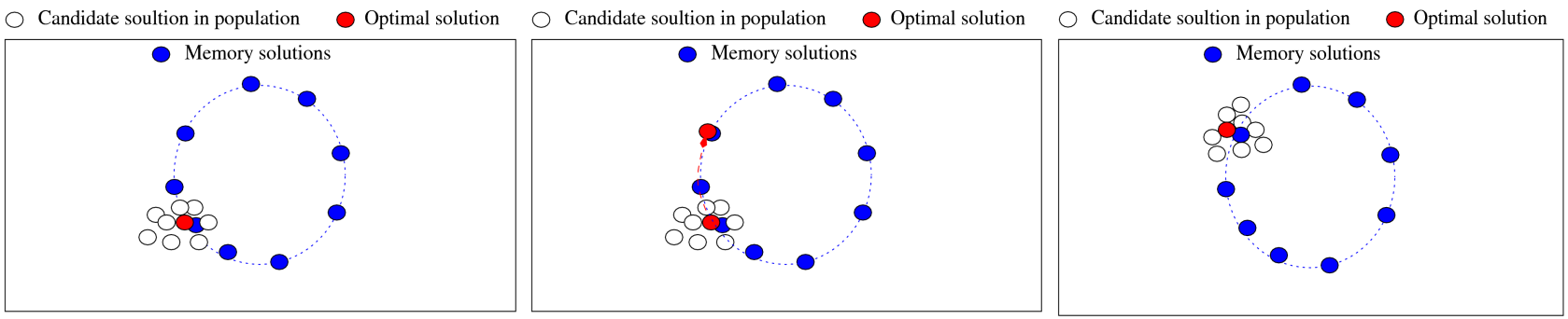
Lewis et al. (1998)

- Each individual has a pair of chromosomes
- Dominance scheme maps genotype to phenotype
- Dominance scheme may change or be adaptive (Uyar & Harmanci, 2005)

Explicit Memory Approaches

Basic idea: use extra memory

- With time, store useful information of the pop into memory
- When a change occurs, use memory to track new optimum



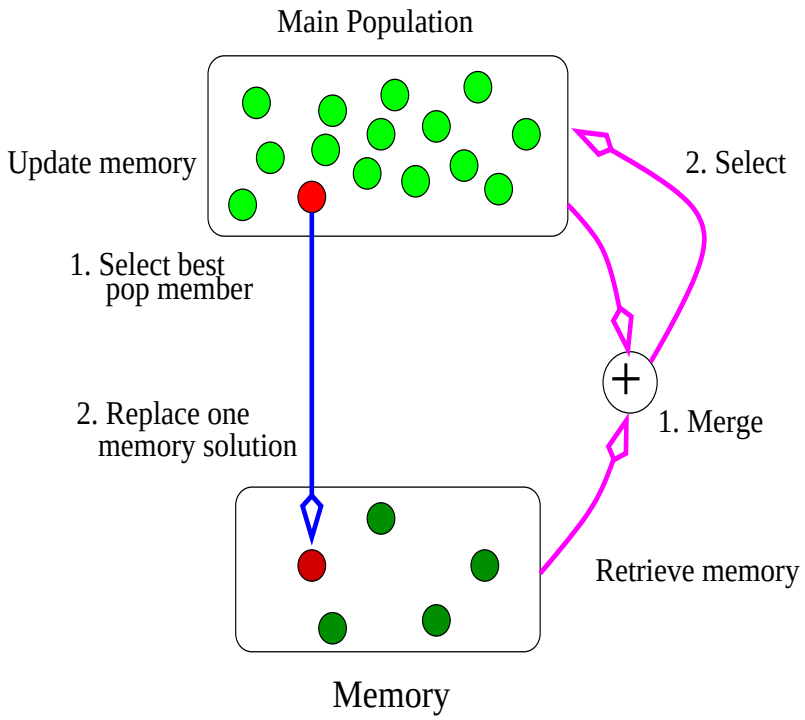
Search space (Memory stores best solutions)

Search space (Optimum moves to next state)

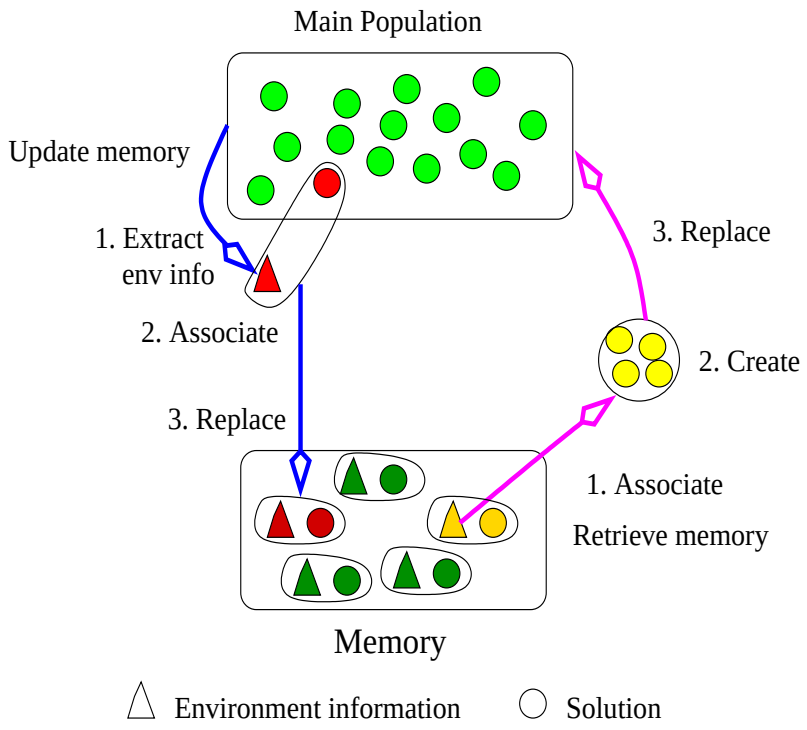
Search space (Population moves to new optimum)

Explicit Memory: Direct vs Associative

- Direct memory: store good solutions (Branke, 1999)
- Associative memory: store environmental information + good solutions (Yang & Yao, 2008)



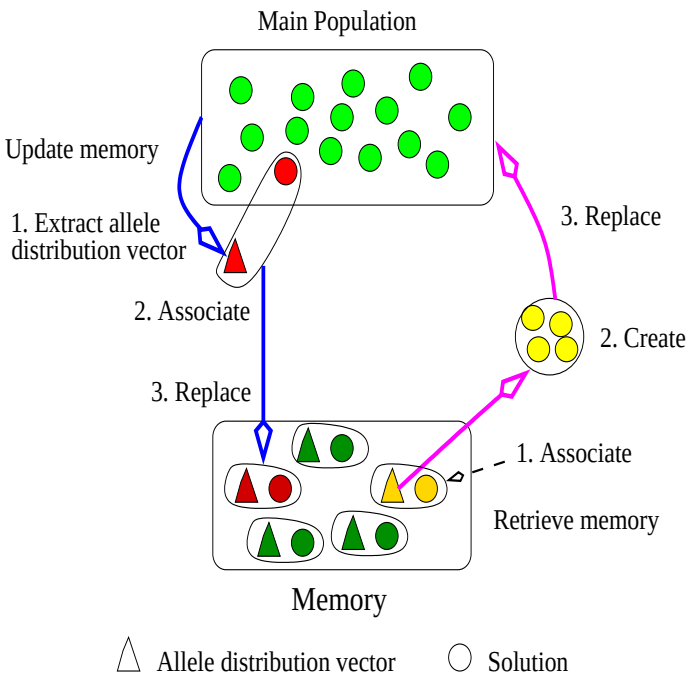
Direct Memory



Associative Memory

Associative Memory Based Genetic Algorithm

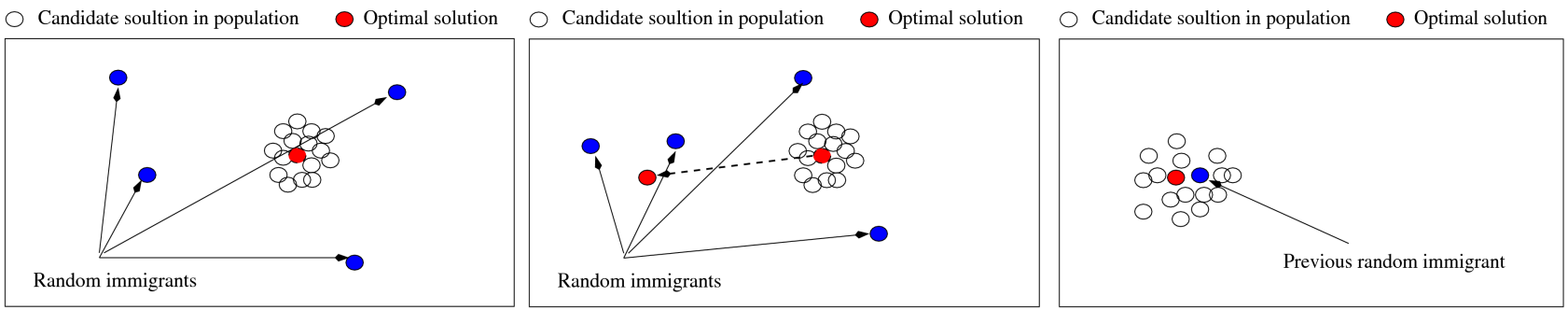
Idea: Use *allele distribution* (AD) $\vec{D}$ to represent environmental info.



- Use memory to store <$\vec{D}$, S> pairs
- Update memory by similarity policy
- Re-evaluate memory every generation. If change detected
  - Extract best memory AD: $\vec{D}_M$
  - Create solutions by sampling $\vec{D}_M$
  - Replace them into the pop randomly
- Details:
  - S. Yang (2006). *EvoWorkshops'06*, pp. 788–799

Diversity Approaches: Random Immigrants

- Convergence is the key problem in metaheuristics for DOPs
- Random immigrants:
  - Each generation, insert some random individuals (called *random immigrants*) into the population to maintain diversity
  - When optimum moves, random immigrants nearby take action to draw the pop to the new optimum



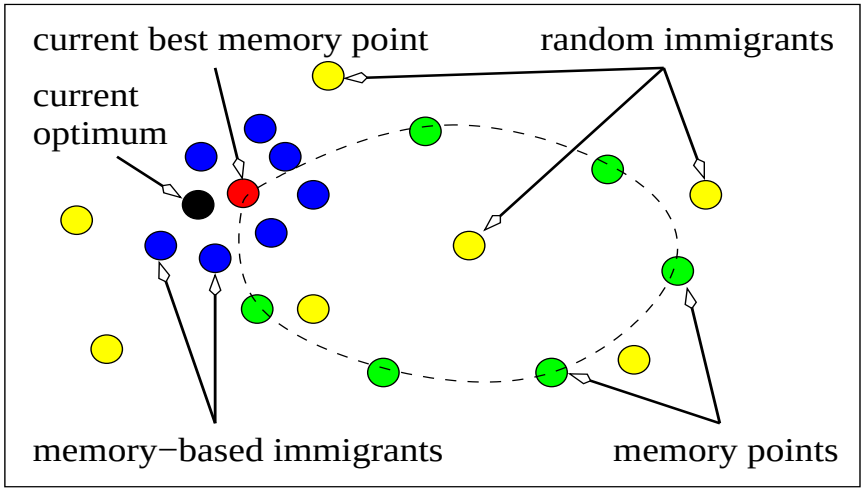
Search Space (Population converging at time t)

Search Space (Optimum moved at time t+1)

Search Space (Population moves to new optimum)

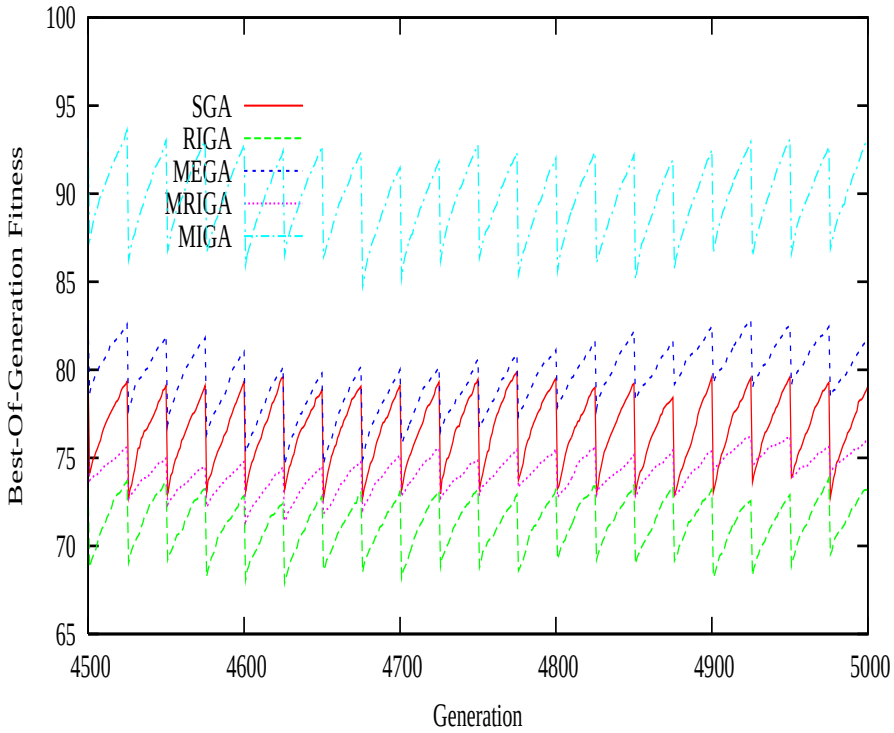
Memory-Based Immigrants

- Random immigrants maintain the diversity while memory adapts an algorithm directly to new environments
- **Memory-based immigrants**: uses memory to guide immigrants towards current environment
  - Re-evaluate the memory every generation
  - Retrieve the best memory point $B_M(t)$ as the base
  - Generate immigrants by mutating $B_M(t)$ with a prob.
  - Replace worst members in the population by these immigrants

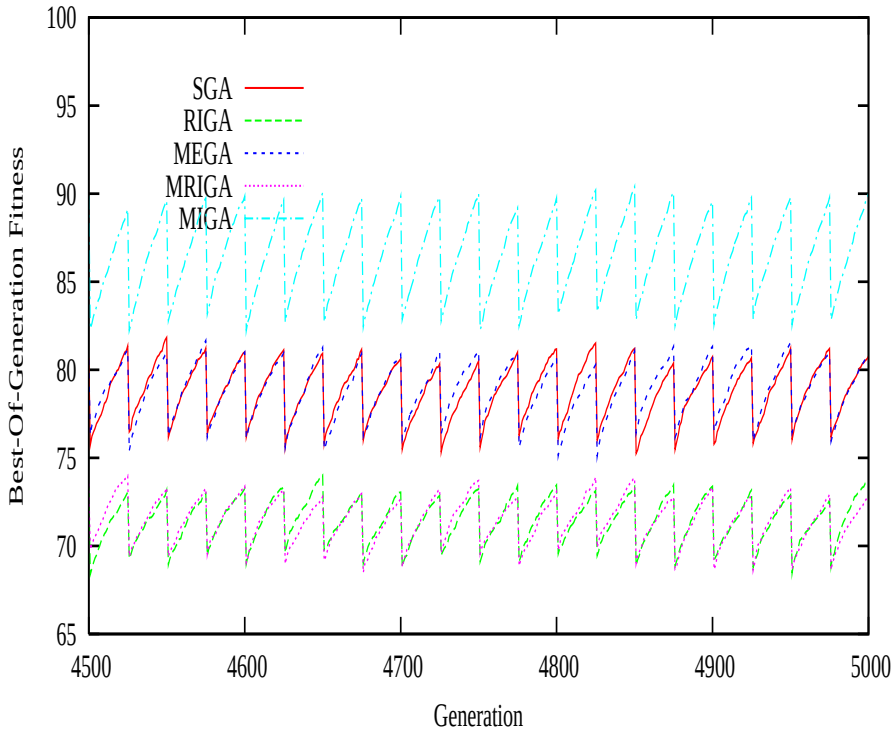


Experimental Results: Immigrants Based GAs

Cyclic Dynamic OneMax Function, $\tau = 25$, $\rho = 0.1$



Random Dynamic OneMax Function, $\tau = 25$, $\rho = 0.1$



- Memory-based immigrants GA (MIGA) significantly beats other GAs
- More details:
  - S. Yang (2008). *Evol. Comput.*, 16(3): 385–416

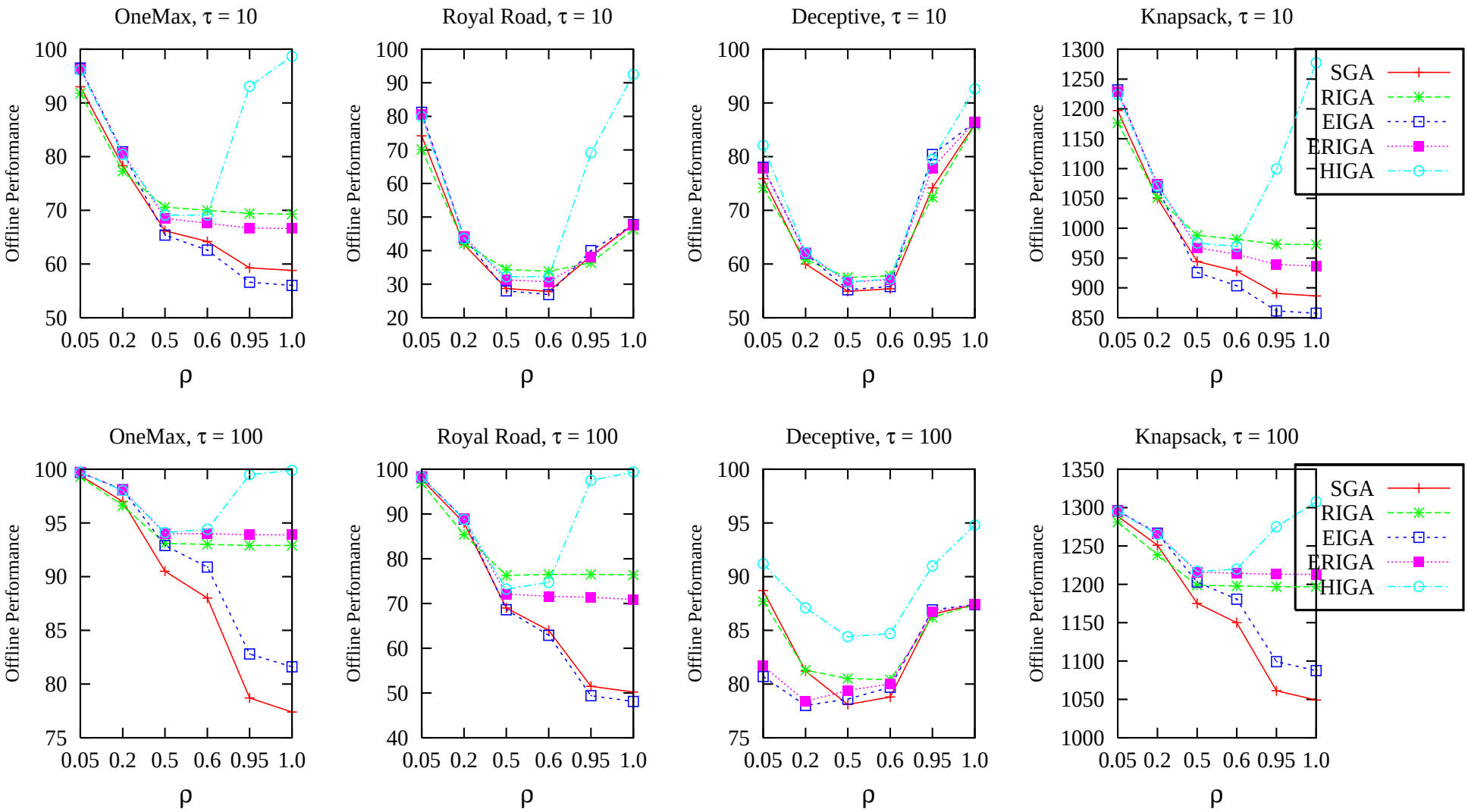
Hybrid Immigrants Approach

- Combines elitism, dualism and random immigrants ideas
- Dualism: Given $\vec{x} = (x_1, \cdots, x_l) \in \{0,1\}^l$, its dual is defined as

$$\vec{x}^d = dual(\vec{x}) = (x_1^d, \cdots, x_l^d) \in \{0,1\}^l$$

  where $x_i^d = 1 - x_i$
- Each generation t, select the best individual from previous generation, $E(t-1)$, to generate immigrants
  - Elitism-based immigrants: Generate a set of individuals by mutating $E(t-1)$ to address slight changes
  - Dualism-based immigrants: Generate a set of individuals by mutating the dual of $E(t-1)$ to address significant changes
  - Random immigrants: Generate a set of random individuals to address medium changes
  - Replace these immigrants into the population
- More details:
  - S. Yang & R. Tinos (2007). *Int. J. of Autom. & Comp.*, 4(3): 243–254

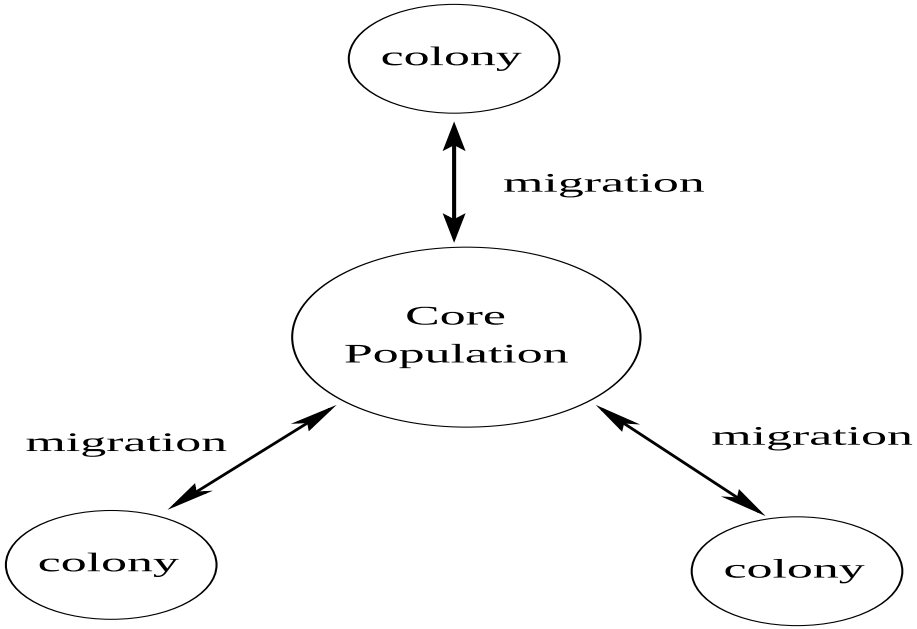
Experimental Results: Hybrid Immigrants GA



- Hybrid immigrants improve GA's performance for DOPs efficiently

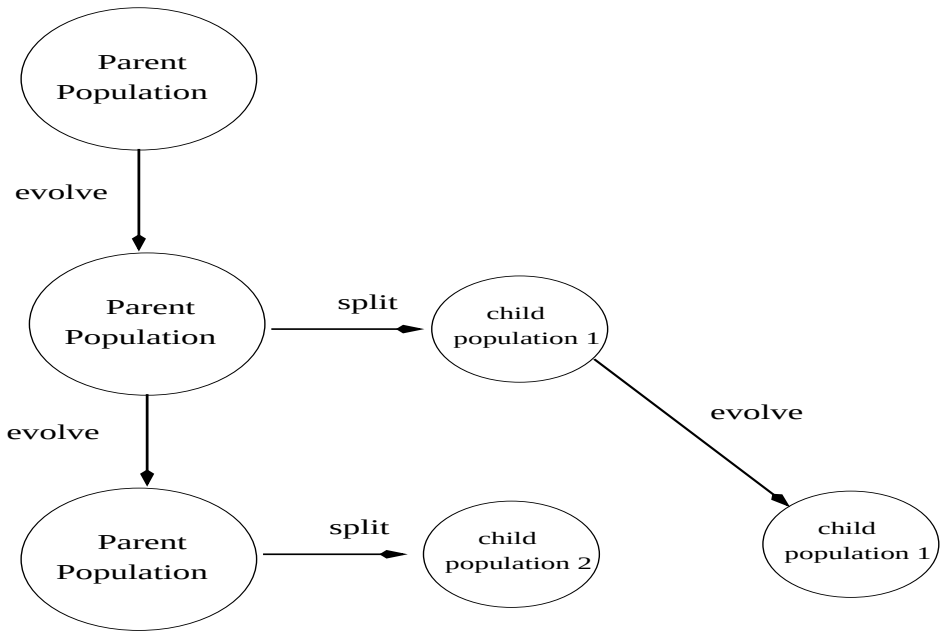
Multi-Populations: Shifting Balance

- Multi-population scheme uses co-operating sub-populations
- Shifting Balance GA (Oppacher & Wineberg, 1999):
  - A core population exploits the promising area
  - Several colonies explore the search space



Multi-Populations: Self-Organizing Scouts

- Self-organizing scouts (SOS) GA (Branke et al., 2000)
  - The parent population explores the search space
  - A child population is split under certain conditions
  - Child populations search limited promising areas



Adaptive Approaches

- Aim: Adapt operators/parameters, usually after a change
  - Hypermutation (Cobb & Grefenstette, 1993): raise the mutation rate temporarily
  - Hyper-selection (Yang & Tinos, 2008): raise the selection pressure temporarily
  - Hyper-learning (Yang & Richter, 2009): raise the learning rate for Population-Based Incremental Learning (PBIL) temporarily
- Combined: Hyper-selection and hyper-learning with re-start or hypermutation

Prediction Approaches

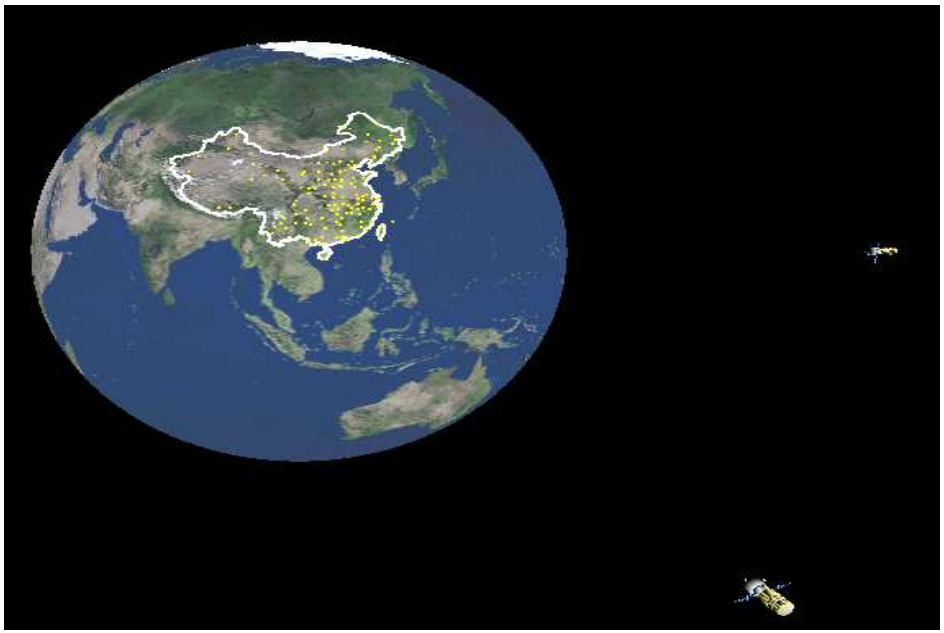
- For some DOPs, changes exhibit predictable patterns
- Techniques (forecasting, Kalman filter, etc.) can be used to predict
  - The location of the next optimum after a change
  - When the next change will occur and which environment may appear
- Some relevant work: see Simões & Costa (2009)

Remarks on Enhancing Approaches

- No clear winner among the approaches
- Memory is efficient for cyclic environments
- Multi-population is good for tracking competing peaks
  - The search ability will decrease if too many sub-populations
- Diversity schemes are usually useful
  - Guided immigrants may be more efficient
- Different interaction exists among the approaches
- Golden rule: balancing exploration & exploitation over time

Case Study: GA for Dynamic TSP

- Dynamic TSP:
  - 144 Chinese cities, 1 geo-stationary saterllite, and 3 mobile satellites
  - Find the path that cycles each city and satellite once with the minimum length over time
- Solver: A GA with memory and other schemes
- More details:
  - C. Li, M. Yang, & L. Kang (2006). *SEAL'06*, LNCS 4247, pp. 236–243



Case Study: GAs for Dynamic Routing in MANETs – 1

- Shortest path routing problem (SPRP) in a fixed network:
  - Find the shortest path between source and destination in a fixed topology
- More and more mobile ad hoc networks (MANETs) appear where the topology keeps changing
- Dynamic SPRP (DSPRP)in MANETs:
  - Find a series of shortest paths in a series of highly-related network topologies
- We model the network dynamics as follows:
  - For each change, a number of nodes are randomly selected to sleep or wake up based on their current status

Case Study: GAs for Dynamic Routing in MANETs – 2

- A specialized GA for the DSPRP:
  - Path-oriented encoding
  - Tournament selection
  - Path-oriented crossover and mutation with repair
- Enhancements: Immigrants and memory approaches
- Experimental results:
  - Both immigrants and memory enhance GA's performance for the DSPRP in MANETs.
  - Immigrants schemes show their power in acyclic environments
  - Memory related schemes work well in cyclic environments
- More details:
  - S. Yang, H. Cheng, & F. Wang (2010). IEEE Trans SMC Part C: Appl. & Rev., 40(1): 52–63

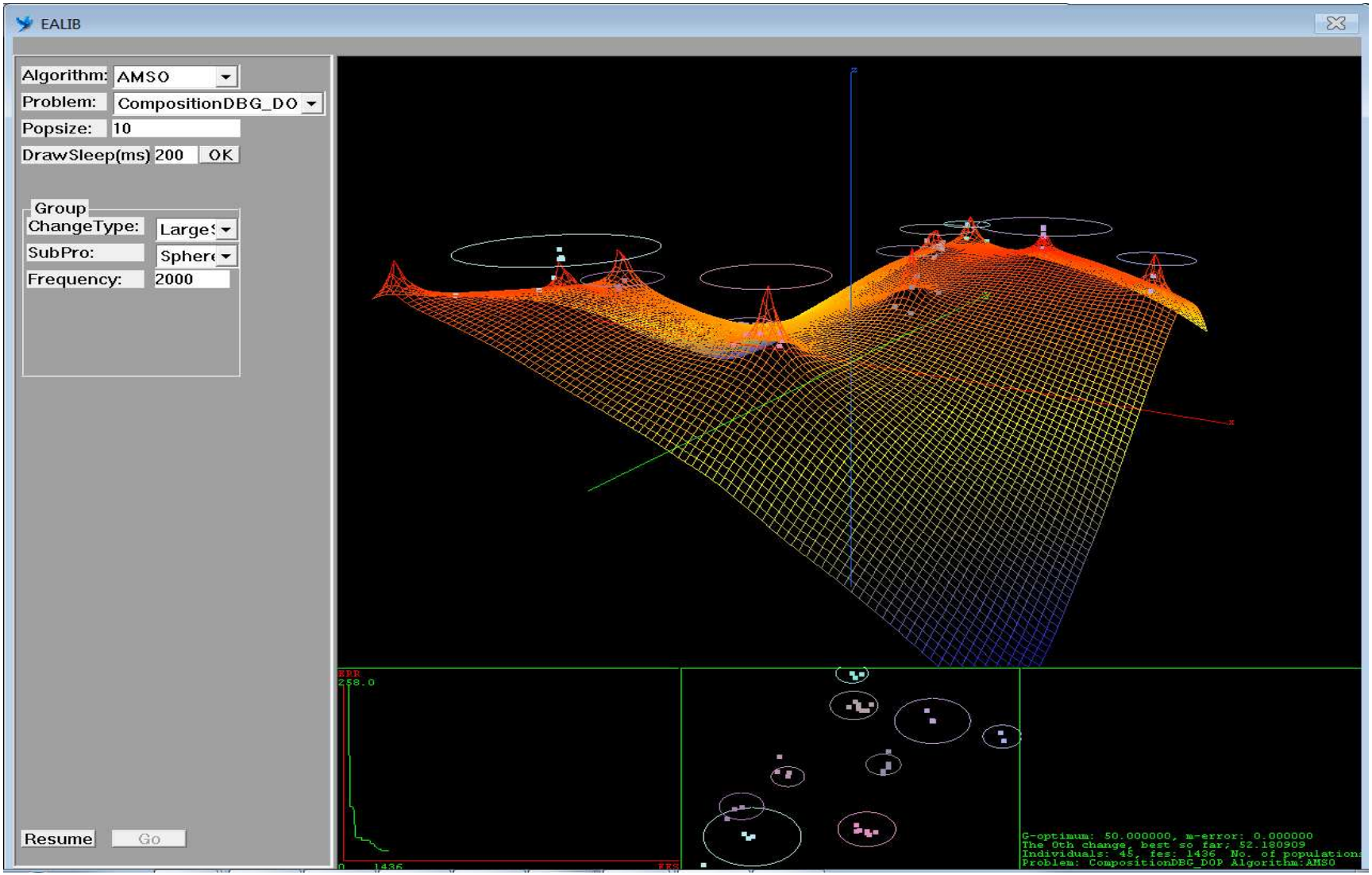
Case Study: PSO for Continuous DOPs

- Particle Swarm Optimization (PSO):
  - Inspired by models of swarming and flocking
  - First introduced by Kennedy and Eberhart in 1995
  - PSO has been applied for many static optimization problems
- Recently, PSO has been applied for continuous DOPs
- Two aspects to consider for DOPs:
  - Outdated memory. Two solutions:
    - Simply set *pbest* to the current position
    - Reevaluate *pbest* and reset it to the current position if current position is better
  - Diversity loss. Three solutions:
    - Introduce diversity after a change
    - Maintain diversity during the run
    - Use multi-swarms

Multi-swarm PSO for DOPs

- Clustering PSO (CPSO):
  - Training: Move particles toward different promising regions
  - Clustering: Single linkage hierarchical clustering to create sub-swarms
  - Local search: Each sub-swarm will search among one peak quickly
  - Overlapping and convergence check
  - Strategies to response to changes
  - Details: Li & Yang, CEC'09; Yang & Li, IEEE Trans Evol Comput, 14(6), 2010
- Adaptive Multi-Swarm Optimizer (AMSO):
  - Use single linkage hierarchical clustering to create populations
  - An overcrowding scheme to remove unnecessary populations
  - A special rule to decide proper moments to increase diversity without change detection
  - An adaptive method to create a proper number of populations needed
  - Details:
    - Li, Yang & Yang (2014), Evol Comput, 22(4): 559–594
    - Li *et al.* (2016), IEEE Trans Evol Comput, 20(4): 590–605

Demo: CPSO & AMSO for DOPs



Case Study: Ant Colony Optimization (ACO) for DOPs

- ACO mimics the behaviour of ants searching for food
- ACO was first proposed for TSPs (Dorigo *et al.*, 1996)
- Generally, ACO was developed to be suitable for graph optimization problems, such as TSP and VRP
- The idea was to let ants “walk” on the arcs of the graph while “reading” and “writing” pheromones until they converge into a path
- Standard ACO consists of two phases:
  - Forward mode: Construct solutions
  - Backward mode: Pheromone update
- Conventional ACO cannot adapt well to DOPs due to stagnation behaviour
  - Once converged, it is hard to escape from the old optimum

ACO for DOPs: General Comments

- ACO transfers knowledge via pheromone
  - Make sense on slight changes; otherwise, may misguide the search
  - For severe changes, a global restart is a better choice
  - A global restart of ACO $\Rightarrow$ pheromone re-initialization
- Moreover, ACO has to maintain adaptability, instead of stagnation behaviour, to accept knowledge transferred
- Recently, many approaches developed with ACO for DOPs (Mavrovouniotis, Li, & Yang 2017)
  - Pheromone modification after a change (Guntsch & Middendorf, 2001, Eyckelhof & Snoek, 2002)
  - Memory-based schemes (Guntsch & Middendorf, 2002)
  - Hybrid and memetic algorithms (Mavrovouniotis, Muller & Yang, 2017)
  - Pheromone modification during execution (Mavrovouniotis & Yang, 2013a)
  - Multi-colony schemes (Mavrovouniotis, Yang & Yao, 2014)

ACO with Pheromone Strategies: Adapting Evaporation

- Pheromone evaporation is an adaptation mechanism in ACO
- Different evaporation rates perform better for different DOPs
- Solution $\Rightarrow$ Adaptive pheromone evaporation rate
  - Starts with an initial ρ and modifies it as follows:
  - When stagnation behaviour is detected, increase ρ to help ants forget current solution; otherwise, decrease ρ to avoid randomization
  - A λ-branching method is used to detect stagnation behaviour
- Performs better than fixed evaporation rate
  - However, a restart strategy performs better for severe changes
- More details:
  - Mavrovouniotis & Yang (2013a) for both DTSP and DVRP

ACO with Pheromone Strategies: Immigrants

- Integrate immigrants schemes to ACO
- A short-term memory is used to store the best k ants and generated immigrant ants
- The memory is updated every iteration
  - No ant can survive in more than one iteration
- Pheromone trails are synchronized with short-term memory
  - Any changes to the memory applied also to pheromone trails
- Pheromone evaporation is not used because pheromone trails are removed directly
- More details:
  - Mavrovouniotis & Yang (2013b) for DTSPs
  - Mavrovouniotis & Yang (2015) for DVRPs
  - Eaton, Mavrovouniotis & Yang (2016) for the dynamic railway junction rescheduling problem

Theoretical Development

- So far, mainly empirical studies
- Theoretical analysis has just appeared
- Runtime analysis:
  - Stanhope & Daida (1999) first analyzed a (1+1) EA on the dynamic bit matching problem (DBMP)
  - Droste (2002) analyzed the first hitting time of a (1+1) ES on the DBMP
  - Rohlfshagen *et al.* (2010) analyzed how the magnitude and speed of change may affect the performance of the (1+1) EA on two functions constructed from the XOR DOP generator
- Analysis of dynamic fitness landscape:
  - Branke *et al.* (2005) analyzed the changes of fitness landscape due to changes of the underlying problem instance
  - Richter (2010) analyzed the properties of spatio-temporal fitness landscapes constructed from Coupled Map Lattices (CML)
  - Tinos and Yang (2010, 2014) analyzed the properties of the XOR DOP generator based on the dynamical system approach of a GA

EC for Dynamic Multi-objective Optimization

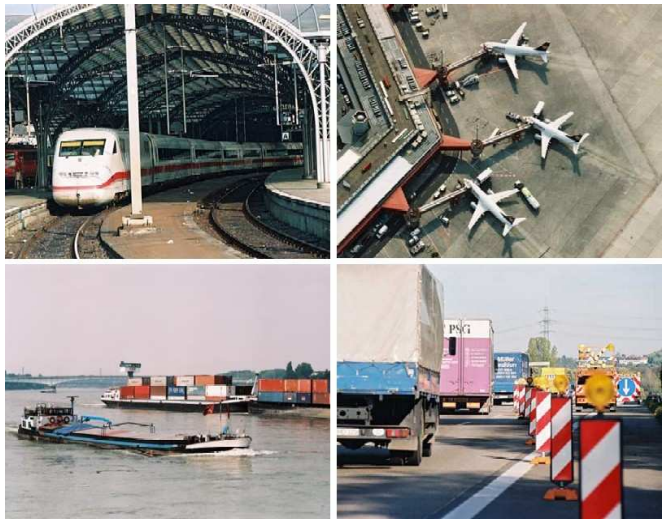
- So far, mainly dynamic single-objective optimization
- Dynamic multi-objective optimization problems (DMOPs): even more challenging
- Recently, rising interest in studying EC for DMOPs
  - Farina *et al.* (2004) classified DMOPs based on the changes on the Pareto optimal solutions
  - Goh & Tan (2009) proposed a competitive-cooperative coevolutionary algorithm for DMOPs
  - Zeng *et al.* (2006) proposed a dynamic orthogonal multi-objective EA (DOMOEA) to solve a DMOP with continuous decision variables
  - Zhang & Qian (2011) proposed an artificial immune system to solve constrained DMOPs
  - Jiang & Yang (2017a) proposed a new benchmark MDOP generator
  - Jiang & Yang (2017b) proposed a Steady-Generational EA (SGEA) for DMOPs
  - Ruan *et al.* (2017) analyzed the effect of diversity maintenance on prediction for DMOPs
  - Eaton *et al.* (2017) applied ACO for the dynamic multi-objective railway junction rescheduling problem

Challenging Issues

- Detecting changes:
  - Most studies assume that changes are easy to detect or visible to an algorithm whenever occurred
  - In fact, changes are difficult to detect for many DOPs
- Understanding the characteristics of DOPs:
  - What characteristics make DOPs easy or difficult?
  - The work has started, but needs much more effort
- Analysing the behaviour of EAs for DOPs:
  - Requiring more theoretical analysis tools
  - Addressing more challenging DOPs and EC methods
  - Big question: Which EC methods for what DOPs?
- Real world applications:
  - How to model real-world DOPs?

Future Work

- The domain has attracted a growing interest recently
  - But, far from well-studied
- New approaches needed: esp. hybrid approaches
- Theoretical analysis: greatly needed
- EC for DMOPs: deserves much more effort
- Real world applications: also greatly needed
  - Fields: logistics, transport, MANETs, data streams, social networks, ...



Summary

- EC for DOPs: challenging but important
- The domain is still young and active:
  - More challenges to be taken regarding approaches, theory, and applications
- More young researchers are greatly welcome!

Acknowledgements

- Two EPSRC funded projects on EC for DOPs
  - “EAs for DOPs: Design, Analysis and Applications”
    - Linked project among Brunel Univ. (Univ. of Leicester before 7/2010), Univ. of Birmingham, BT, and Honda
    - Funding/Duration: over £600K / 3.5 years (1/2008–7/2011)
    - http://gtr.rcuk.ac.uk/project/B807434B-E9CA-41C7-B3AF-567C38589BAC
  - “EC for Dynamic Optimisation in Network Environments”
    - Linked project among DMU, Univ. of Birmingham, RSSB, and Network Rail
    - Funding/Duration: $\sim$£1M / 4.5 years (2/2013–8/2017)
    - http://gtr.rcuk.ac.uk/project/C43F34D3-16F1-430B-9E1F-483BBADCD8FA
- Research team members:
  - Research Fellows: Dr. Hui Cheng, Dr. Crina Grosan, Dr. Changhe Li, Dr. Michalis Mavrovouniotis, Dr. Yong Wang, etc.
  - PhD students: Changhe Li, Michalis Mavrovouniotis, Shouyong Jiang, Jayne Eaton, Hongfeng Wang, etc.
- Research cooperators:
  - Prof. Xin Yao, Prof. Juergen Branke, Prof. Jinliang Ding, Dr. Renato Tinos, Dr. Hendrik Richter, Dr. Trung Thanh Nguyen, etc.

Relevant Information

- IEEE CIS Task Force on EC in Dynamic and Uncertain Environments
  - `http://www.tech.dmu.ac.uk/~syang/IEEE_ECIDUE.html`
  - Maintained by Shengxiang Yang
- Source codes:
  - `http://www.tech.dmu.ac.uk/~syang/publications.html`
- IEEE Competitions:
  - 2009 Competition on EC in Dynamic & Uncertain Environments: `http://www.cs.le.ac.uk/people/syang/ECiDUE/ECiDUE-Competition09`
  - 2012 Competition on EC for DOPs: `http://people.brunel.ac.uk/~csstssy/ECDOP-Competition12.html`

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