Evolutionary Computation for Dynamic Optimization Problems

Shengxiang Yang

Centre for Computational Intelligence
School of Computer Science and Informatics
De Montfort University, United Kingdom
Email: syang@dmu.ac.uk
http://www.tech.dmu.ac.uk/∼syang

Tutorial presented at the 2018 IEEE Congress on Evolutionary Computation (IEEE CEC 2018), Rio de Janeiro, Brazil, 8-13 July, 2018

DE MONTFORT UNIVERSITY LEICESTER

IEEE Computational Intelligence Society

Presenter — Shengxiang Yang

- Education and career history:
  - PhD, Northeastern University, China, 1999
  - Worked at King's College London, University of Leicester, and Brunel University, UK, 1999-2012
  - Joined De Montfort University (DMU), UK 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 250 publications and £2M funding for research

- AE/Editorial Board Member for 7 journals, including *IEEE Trans Cybern*, *Evol Comput*, *Inform Sci*, and *Soft Comput*

- Ex-Chair of two IEEE CIS Task Forces
  - EC in Dynamic and Uncertain Environments (2011-2017)
  - Intelligent Network Systems (2012-2017)

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, 20+ 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, RSSB, Network Rail, BT, Honda, 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

Black Box Solver

Problem to solve ⟶ Evolutionary Algorithm ⟶ A set of soultions
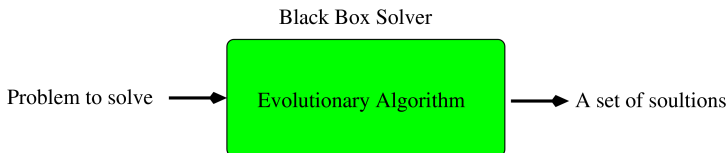
Design and Framework of an EA

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

- Representation of solution into individual
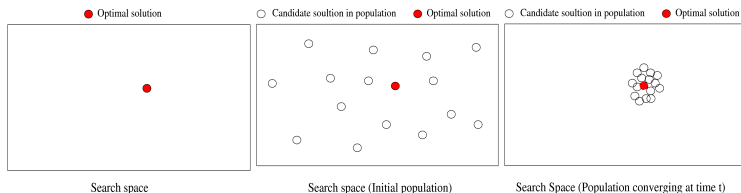- Evaluation or fitness function

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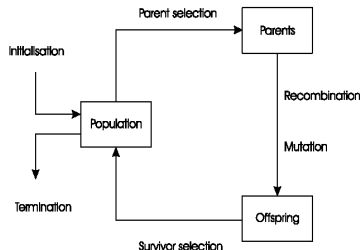
- EAs are easy-to-use: No strict requirements to problems
- Widely used for optimisation and search problems
  - Financial and economical systems
  - Transportation and logistics systems
  - Industry engineering
  - Automatic programming, art and music design
  - ......

EC for Optimisation Problems

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

● Optimal solution	○ Candidate soultion in population ● Optimal solution	○ Candidate soultion in population ● Optimal solution
Search space	Search space (Initial population)	Search Space (Population converging at time t)

- 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

Search Space (Population converging at time t)

Search Space (Optimum moved at time t+1)
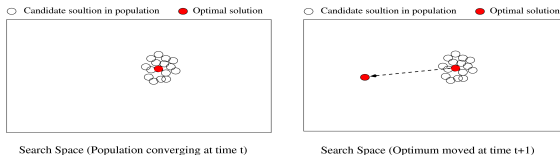
- DOPs challenge traditional EAs
  - Once converged, hard to escape from an old optimum

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:
    - Eaton, 2017; Abdallah, 2017; Jiang, 2017; Christopher, 2015; 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 (2004–2018): part of Evo*
    - ECiDUE (2004–2018): part of IEEE CEC
    - EvoDOP ('99, '01, '03, '05, '07, '09): part of GECCO
- IEEE Symposium on CIDUE (2011, 2013-2018)
- IEEE Competitions: with IEEE CEC'09, CEC'12, CEC'14, CEC'15 & CEC'18

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 ≥ 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:

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

  – $\vec{x} = (x_1, \cdots, x_D)$: 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:

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

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

- The dynamics:

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

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

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

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

– $\sigma \sim N(0, 1)$; 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

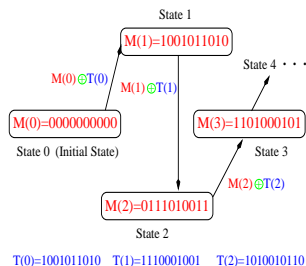# Dynamic Knapsack Problems (DKPs)

- 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:

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

  – $\vec{x}(t) \in \{0, 1\}^n$: 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
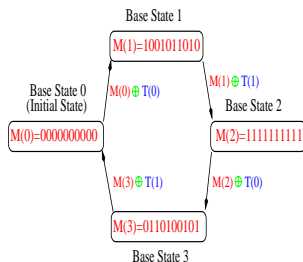- For each environmental period $k = \lfloor t/\tau \rfloor$, do:

State 1
M(1)=1001011010

M(0)⊕T(0)   M(1)⊕T(1)   State 4 · · ·

M(0)=0000000000   M(3)=1101000101

State 0 (Initial State)   State 3

M(2)⊕T(2)

M(2)=0111010011

State 2

T(0)=1001011010   T(1)=1110001001   T(2)=1010010110

1. Create a template T_k with $\rho * l$ ones
2. Create a mask $\vec{M}(k)$ incrementally
   $$\vec{M}(0) = \vec{0} \quad \text{(the initial state)}$$
   $$\vec{M}(k+1) = \vec{M}(k) \oplus \vec{T}(k)$$
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

Can extend the XOR DOP generator to create cyclic environments:

Partition Templates: T(0)=1001011010   v   T(1)=0110100101

Base State 1

M(1)=1001011010

M(1) ⊕ T(1)

Base State 0
(Initial State)

M(0) ⊕ T(0)

Base State 2

M(0)=0000000000

M(2)=1111111111

M(3) ⊕ T(1)

M(2) ⊕ T(0)

M(3)=0110100101

Base State 3

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

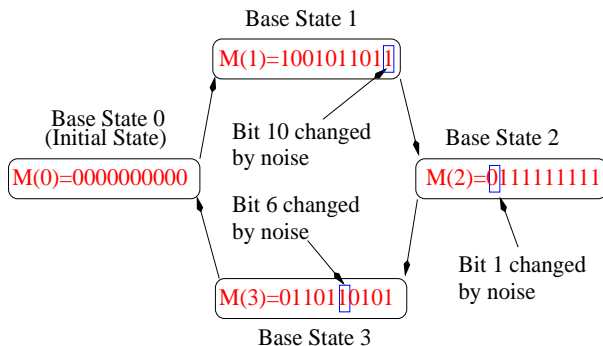$$f(\vec{x}, t) = f(\vec{x} \oplus \vec{M}(I_t)) = f(\vec{x} \oplus \vec{M}(k\%(2K)))$$

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

– $I_t = k\%(2K)$: mask index

We can also construct cyclic environments with noise:

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

Base State 1

M(1)=1001011011

Base State 0
(Initial State)

M(0)=0000000000

Bit 10 changed
by noise

Base State 2

M(2)=0111111111

Bit 6 changed
by noise

Bit 1 changed
by noise

M(3)=0110110101

Base State 3

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
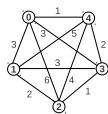 - DTSP can be defined as $f(x, t)$:

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

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

- The dynamic benchmark generator for permutation-encoded problems (DBGP) can create a DOP from any stationary TSP/VRP by swapping objects:
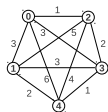
Optimum -> (0,4,3,2,1,0) = 9

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

Evolutionary Algorithms

Population of Individuals

1 = (0,1,3,4,2,0) = **18**
2 = (1,4,2,3,0,1) = **16**
3 = (0,4,3,2,1,0) = **9**
.
.
.

μ = (3,0,4,2,1,3) = **15**

Dynamic Change — — — — — — ▶

Population of Individuals

1 = (0,1,3,4,2,0) = **12**
2 = (1,4,2,3,0,1) = **16**
3 = (0,4,3,2,1,0) = **15**
.
.
.

μ = (3,0,4,2,1,3) = **21**

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:
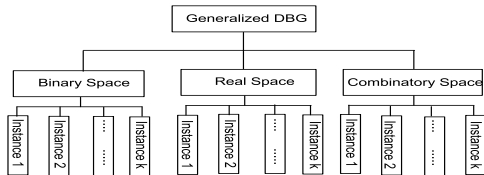
- In GDBG, DOPs are defined as:

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

– 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):

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

– 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)

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

- Accuracy (Trojanowski and Michalewicz, 1999)

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

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

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

- 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

○ Candidate soultion in population   ● Optimal solution

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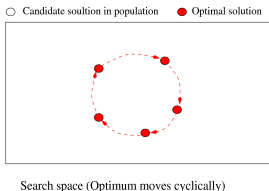
- Memory works by storing and reusing useful information
- Two classes regarding how to store information
  - Implicit memory: uses redundant representations
    - Multiploidy and dominance (Ng & Wong, 1995; Lewis et al., 1998)
    - Dualism mechanisms (Yang, 2003; Yang & Yao, 2005)
  - Explicit memory: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

Encoding
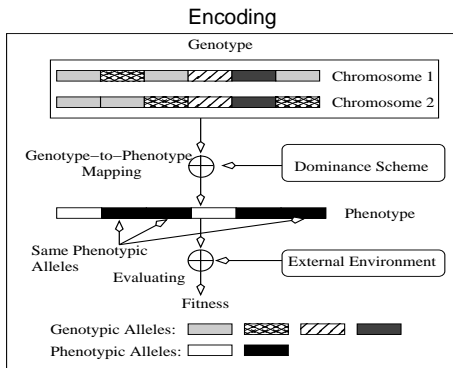
Dominance Scheme

	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)

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)
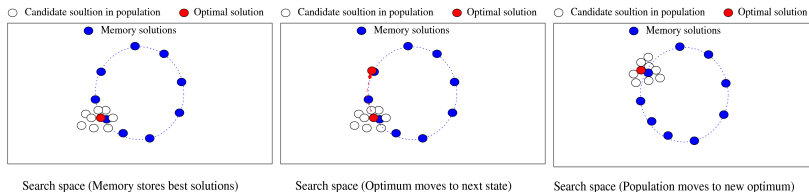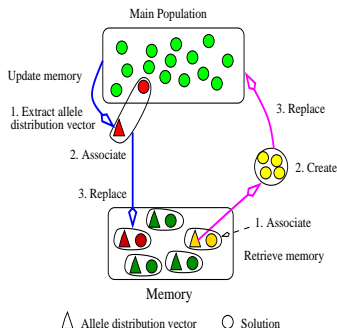
Explicit Memory: Direct vs Associative

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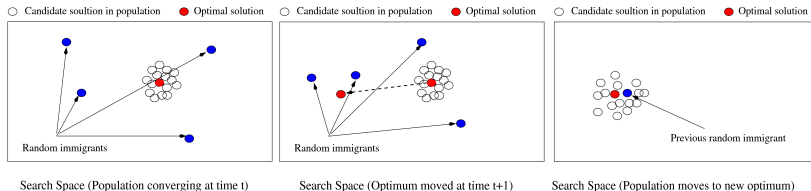

Direct Memory

Associative Memory

$\triangle$ Environment information $\bigcirc$ Solution
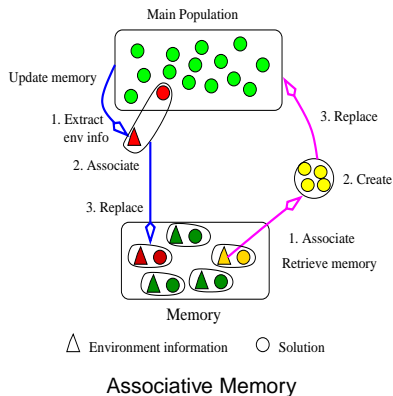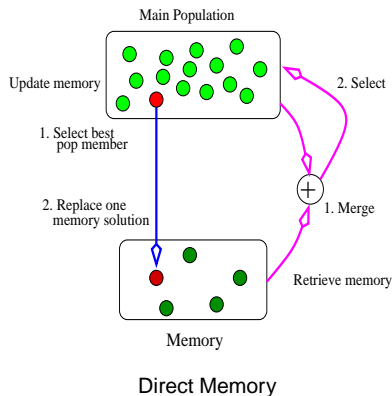
Associative Memory Based Genetic Algorithm

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

Main Population

Update memory

1. Extract allele distribution vector

2. Associate

3. Replace

3. Replace

2. Create

1. Associate

Retrieve memory

Memory

△ Allele distribution vector   ○ Solution

- 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.
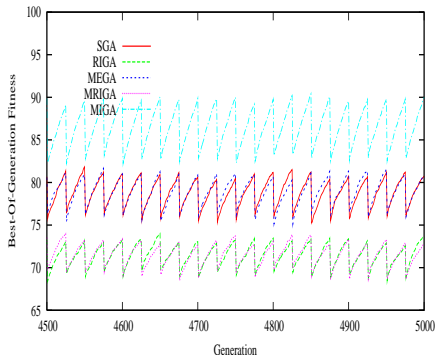 - Replace worst members in the population by these immigrants

current best memory point   random immigrants

current optimum

memory−based immigrants   memory points

Search Space
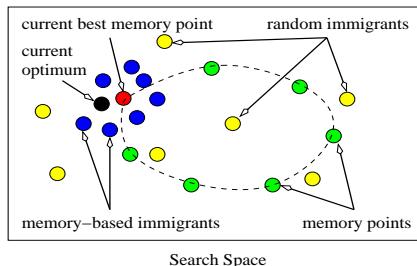
Experimental Results: Immigrants Based GAs

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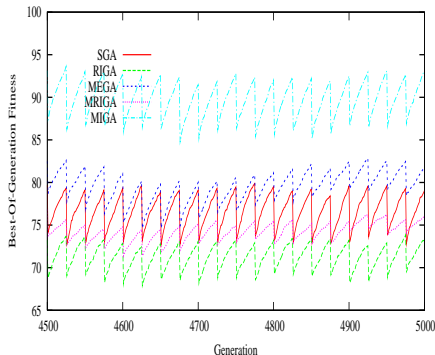
Random Dynamic OneMax Function, $\tau = 25$, $\rho = 0.1$

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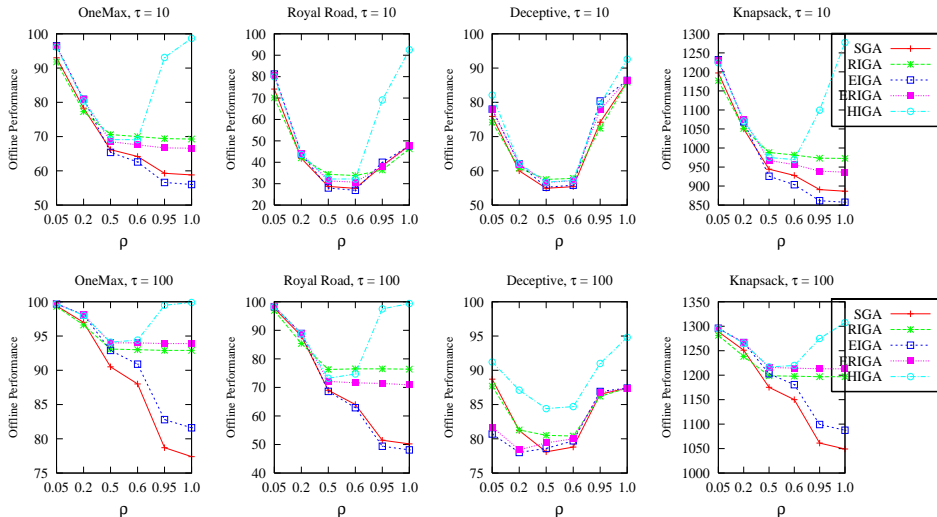
Hybrid Immigrants Approach

- 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
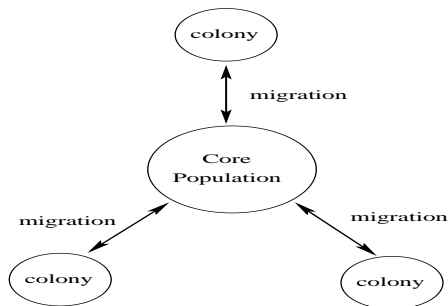
Experimental Results: Hybrid Immigrants GA

- 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

- 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
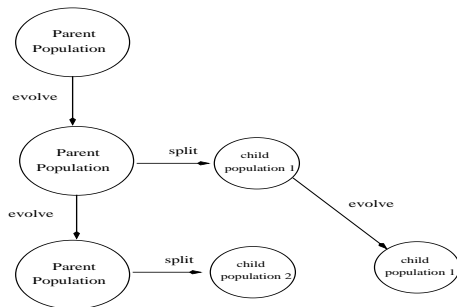
- Aim: Adapt operators/parameters, usually after a change
  - Hypermutation (Cobb & Grefenstette, 1993): raise the mutation rate temporarily
  - Hyper-selection (Yang & Tinos, 2008): raise the selection pressure temporarily
  - Hyper-learning (Yang & Richter, 2009): raise the learning rate for Population-Based 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
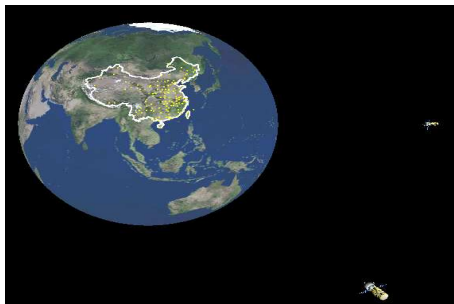
- Shortest path routing problem (SPRP) in a fixed network:
    - Find the shortest path between source and destination in a fixed topology
- More and more mobile ad hoc networks (MANETs) appear where the topology keeps changing
- Dynamic SPRP (DSPRP)in MANETs:
    - Find a series of shortest paths in 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

- 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
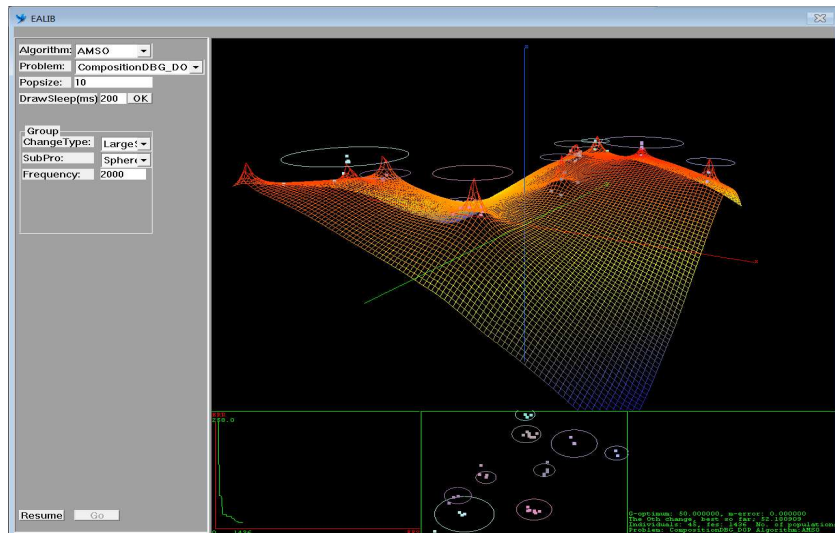
Case Study: Ant Colony Optimization (ACO) for DOPs

- 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: ~£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://ieee-tf-ecidue.cug.edu.cn/
  - Maintained by Dr. Changhe Li
- 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

References – 1

1. E. Alba, A. Nakib, & P. Siarry (2013). Metaheuristics for Dynamic Optimization. Springer
2. J. Branke (1999). Memory enhanced evolutionary algorithms for changing optimization problems. *CEC'99*, pp. 1875–1882
3. J. Branke (2002). *Evolutionary Optimization in Dynamic Environments*. Kluwer Academic Publishers
4. J. Branke, E. Salihoglu, S. Uyar (2005). Towards an analysis of dynamic environments. *GECCO'05*, pp. 1433–1439
5. H.G. Cobb, J.J. Grefenstette (1993). Genetic algorithms for tracking changing environments. *Proc. ICGA*, pp. 523–530
6. C. Cruz, J. Gonzanlez, D. Pelta (2011). Optimization in dynamic environments: A survey on problems, methods and measures. *Soft Comput.*, 15: 1427–1448
7. M. Dorigo, V. Maniezzo, A. Colorni (1996). Ant system: Optimization by a colony of cooperating agents, IEEE Trans SMC-Part B: Cybern 26(1): 29–41
8. S. Droste (2002). Analysis of the (1+1) EA for a dynamically changing onemax-variant. *CEC'02*, pp. 55–60
9. J. Eaton, S. Yang, M. Gongora (2017). Ant colony optimization for simulated dynamic multi-objective railway junction rescheduling. IEEE Trans on ITS, 18(11): 2980–2992
10. J. Eaton, S. Yang, M. Mavrovouniotis (2016). Ant colony optimization with immigrants schemes for the dynamic railway junction rescheduling problem with multiple delays. Soft Comput, 20(8): 2951–2966
11. C. Eyckelhof, M. Snoek (2002). Ant systems for a dynamic TSP, *Proc 3rd Int Workshop on Ant Algorithms*, LNCS 2463, pp. 88–99
12. M. Farina, K. Deb, P. Amato (2004). Dynamic multiobjective optimization problems: test cases, approximations, and applications. *IEEE Trans Evol Comput*, 8(5): 425–442

References – 2

13 C. Goh, K.C. Tan (2009). A competitive-cooperative coevolutionary paradigm for dynamic multiobjective optimization. *IEEE Trans Evol Comput*, 13(1): 103–127

14 M. Guntsch, M. Middendorf (2001). Pheromone modification strategies for ant algorithms applied to dynamic TSP, *EvoWorkshops 2001*, LNCS 2037, pp. 213–222

15 M. Guntsch, M. Middendorf (2002). Applying population based aco to dynamic optimization problems, *Proc. 3rd Int. Workshop on Ant Algorithms*, LNCS 2463, pp. 111–122

16 M. Guntsch, M. Middendorf, H. Schmeck (2001). An ant colony optimization approach to dynamic TSP, *GECCO 2001*, pp. 860–867

17 S. Jiang, S. Yang (2017a). Evolutionary dynamic multi-objective optimization: benchmarks and algorithm comparisons. IEEE Trans Cybern, 47(1): 198-211

18 S. Jiang, S. Yang (2017b). A steady-state and generational evolutionary algorithm for dynamic multi-objective optimization. IEEE Trans Evol Comput, 21(1): 65-82.

19 Y. Jin, J. Branke (2005). Evolutionary optimization in uncertain environments–A survey. *IEEE Trans Evol Comput*, 9(3): 303–317

20 R.W. Morrison (2004). *Designing Evolutionary Algorithms for Dynamic Environments*. Springer

21 E.H.J. Lewis, G. Ritchie (1998). A comparison of dominance mechanisms and simple mutation on non-stationary problems. *PPSN V*, pp. 139–148

22 C. Li, S. Yang, M. Yang (2014). An adaptive multi-swarm optimizer for dynamic optimization problems. Evol Comput, 22(4): 559–594

23 C. Li, T.T. Nguyen, M. Yang, M. Mavrovouniotis, S. Yang (2016). An adaptive multi-population framework for locating and tracking multiple optima. IEEE Trans Evol Comput, 20(4): 590–605

References – 3

24 M. Mavrovouniotis, C. Li, S. Yang (2017). A survey of swarm intelligence for dynamic optimization: Algorithms and applications. Swarm & Evol Comput, 33: 1–17

25 M. Mavrovouniotis, F.M. Muller, S. Yang (2017). Ant colony optimization with local search for dynamic travelling salesman problems. IEEE Trans Cybern, 47(7): 1743–1756

26 M. Mavrovouniotis, S. Yang (2013a). Adapting the pheromone evaporation rate in dynamic routing problems, EvoApplications 2013, LNCS 7835, pp. 606–615

27 M. Mavrovouniotis, S. Yang (2013b). Ant colony optimization with immigrants schemes for the dynamic travelling salesman problem with traffic factors, Appl. Soft Comput, 13(10): 4023–40376.

28 M. Mavrovouniotis, S. Yang (2015). Ant algorithms with immigrants schemes for the dynamic vehicle routing problem. Inform Sci, 294: 456–477

29 M. Mavrovouniotis, S. Yang, X. Yao (2012). A benchmark generator for dynamic permutation-encoded problems, PPSN XII, LNCS 7492, pp. 508–517

30 M. Mavrovouniotis, S. Yang, X. Yao (2014). Multi-colony ant algorithms for the dynamic travelling salesman problem, *IEEE SSCI 2014*, pp. 9–16

31 R. Montemanni, L. M. Gambardella, A. E. Rizzoli, A. V. Donati (2005). Ant colony system for a dynamic vehicle routing problem, Combinat Optim, 10: 327–343

32 R.W. Morrison, K.A. De Jong (1999). A test problem generator for non-stationary environments. *CEC'99*, pp. 2047–2053

33 K.P. Ng, K.C. Wong (1995). A new diploid scheme and dominance change mechanism for non-stationary function optimisation. *ICGA 6*, pp. 159–166

34 T.T. Nguyen, S. Yang, J. Branke (2012). Evolutionary dynamic optimization: A survey of the state of the art. *Swarm & Evol Comput*, 6: 1–24

References – 4

35 F. Oppacher, M. Wineberg (1999). The Shifting balance genetic algorithm: Improving the GA in a dynamic environment. *GECCO'99*, vol. 1, pp. 504–510

36 G. Ruan, G. Yu, J. Zheng, J. Zou, S. Yang (2017). The effect of diversity maintenance on prediction in dynamic multi-objective optimization. Appl Soft Comput, 58: 631–647.

37 H. Richter (2010). Evolutionary optimization and dynamic fitness landscapes: From reaction-diffusion systems to chaotic cml. *Evolutionary Algorithms and Chaotic Systems*, Springer, pp. 409–446.

38 P. Rohlfshagen, P.K. Lehre, X. Yao (2009). Dynamic evolutionary optimisation: An analysis of frequency and magnitude of change. *GECCO'09*, pp. 1713–1720

39 S.A. Stanhope, J.M. Daida (1999). (1+1) genetic algorithm fitness dynamics in a changing environments. *CEC'99*, vol. 3, pp. 1851–1858

40 R. Tinos, S. Yang (2010) An analysis of the XOR dynamic problem generator based on the dynamical system. *PPSN XI*, LNCS 6238, Part I, pp. 274–283

41 R. Tinos, S. Yang (2014). Analysis of fitness landscape modifications in evolutionary dynamic optimization. *Inform Sci*, 282: 214–236

42 A. Simões, E. Costa (2009). Improving prediction in evolutionary algorithms for dynamic environments. *GECCO'09*, pp. 875–882

43 K. Trojanowski, Z. Michalewicz (1999). Searching for optima in non-stationary environments. *CEC'99*, vol. 3, pp. 1843–1850

44 A.S. Uyar, A.E. Harmanci (2005). A new population based adaptive domination change mechanism for diploid genetic algorithms in dynamic environments. *Soft Comput*, 9: 803–814

45 S. Yang (2003). Non-stationary problem optimization using the primal-dual genetic algorithm. *CEC'03*, pp. 2246–2253

References – 5

46. S. Yang, Y. Jiang, T.T. Nguyen (2013). Metaheuristics for dynamic combinatorial optimization problems. *IMA J of Management Math*, 24(4): 451–480

47. S. Yang, C. Li (2010). A clustering particle swarm optimizer for locating and tracking multiple optima in dynamic environments. IEEE Trans Evol Comput, 14(6): 959–974

48. S. Yang, Y.-S. Ong, Y. Jin (2007). *Evolutionary Computation in Dynamic and Uncertain Environments*. Springer

49. S. Yang, H. Richter (2009). Hyper-learning for population-based incremental learning in dynamic environments. *CEC'09*, pp. 682–689

50. S. Yang, R. Tinos (2008). Hyper-selection in dynamic environments. *CEC'08*, pp. 3185–3192

51. S. Yang, X. Yao (2005). Experimental study on population-based incremental learning algorithms for dynamic optimization problems. *Soft Comput*, 9: 815–834

52. S. Yang, X. Yao (2008). Population-based incremental learning with associative memory for dynamic environments. *IEEE Trans Evol Comput*, 12: 542–561

53. S. Yang, X. Yao (2013). *Evolutionary Computation for Dynamic Optimization Problems*. Springer

54. K. Weicker (2003). *Evolutionary Algorithms and Dynamic Optimization Problems*. Der Andere Verlag

55. S. Zeng et al. (2006). A dynamic multi-objective evolutionary algorithm based on an orthogonal design. *CEC'06*, pp. 573–580

56. Z. Zhang, S. Qian (2011). Artificial immune system in dynamic environments solving time-varying non-linear constrained multi-objective problems. *Soft Comput*, 15(7): 1333–1349