

Dual Phase Evolution

David G. Green · Jing Liu
Hussein A. Abbass

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David G. Green
Faculty of Information Technology
Monash University Centre for Research
on Intelligent Systems
Clayton
Australia

Hussein A. Abbass
School of Engineering and Information
Technology
University of New South Wales
Canberra, ACT
Australia

Jing Liu
Key Laboratory of Intelligent Perception
and Image Understanding of Ministry
of Education
Xidian University
Xi'an
People's Republic of China

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To our families and students

Preface

As computers have become all-pervasive in modern society, the growing preoccupation of modern society with information has led to a new paradigm for viewing the world around us. *Natural computation* is the idea of regarding objects and processes in the natural world as forms of computation. There is much evidence to support this view. The genetic code is akin to a tape containing processing instructions and ribosomes are almost literally devices within the cell that read input from an RNA tape and output proteins. Plants grow in a regular, organized way. Simple organisms behave almost like robots. Vision and other senses provide inputs to the brain, which has been likened to a computer, processing information and determining behavior as its outputs.

The natural computation paradigm has provided many new insights about living systems. For instance, simulation studies have shown that the organization of social insect colonies emerges spontaneously as a result of interactions between the insects and their environment.

Perhaps the greatest practical benefit of the idea of natural computation has been to serve as a source of inspiration for computer science. Over millions of years, nature has evolved ways of solving many kinds of complex problems. As problems in computation have grown ever large and more complex, natural solutions provide useful hints. One result is a host of new fields of computer science research that are biologically inspired. They include fields such as Artificial Life, Cellular Automata, Evolutionary Computation, Artificial Neural Networks and Swarm Intelligence.

Dual Phase Evolution (DPE), the central theme of this book, is an important outcome of research into natural computation. It describes a family of processes that lead to self-organization in complex adaptive systems. It not only occurs in species evolution, but also in a wide range of natural and artificial systems. Although the specific details of these systems vary enormously, they all share common underlying features. The most important of these are that they exhibit repeated phase changes, with different processes (selection and variation) operating in the two phases.

This book focuses on both the theory and the applications of DPE. The opening chapters provide an introduction to essential elements of theory. Because DPE is a process that operates within complex adaptive systems, it is necessary to have a clear picture of the essential ideas and issues involved. We explain some key ideas in complexity theory as well as essential issues concerning networks. DPE is then

introduced to provide an overview of its role in various natural and artificial systems. Several models that have been used to investigate how DPE influences different kinds of systems, particularly social networks, are discussed. Several chapters demonstrate the computational use of DPE in new methods for problem solving. Starting with a new network generation model based on DPE, namely DPE-Nets, DPE demonstrates how to reproduce many properties presented by real world networks. The evolutionary dynamics of DPE-Nets and how the properties of DPE-Nets affect fundamental systems dynamics are investigated to have a better understanding on the potential of DPE-Nets for optimization. DPE is then used to develop a new evolutionary algorithm, namely Dual Phase Evolutionary Algorithm (DPEA).

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David G. Green
Jing Liu
Hussein A. Abbass

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Acronyms

AC	Adaptive cycle
AI	Artificial intelligence
ALife	Artificial life
ANN	Artificial neural networks
BA model	Barábasi–Albert model
BTS	Binary tournament selection
CA	Cellular automata
CASs	Complex adaptive systems
CGAs	Cellular genetic algorithms
DDNJ	DNA Database of Japan
DPE	Dual phase evolution
DPEAs	Dual phase evolutionary algorithms
DPE-Nets	Dual phase evolution networks
EAs	Evolutionary algorithms
EC	Evolutionary computation
EMBL	European Molecular Biology Laboratory
ER Model	Erdős–Rényi model
FSM	Finite state machines
GAs	Genetic algorithms
GI	Global interaction
GRNs	Genetic regulatory networks
KC-complexity	Kolmogorov–Chaitin measure of complexity
LI	Local interaction
LRS	Linear ranking selection
LUS	Local uniform selection
NFFEs	Number of fitness function evaluations
NRS	New random sweep
OO	Object-oriented
SA	Simulated annealing
SOC	Self-organized criticality
SR	Success rate
UC	Uniform choice

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Symbols

E	The set of edges in a network
V	The set of vertices in a network
G	A graph
N	Population size; the number of vertices in networks
M	The number of edges in networks
v_i	$v_i \in V$, where $1 \leq i \leq N$
k_i	The degree of node v_i
N_v	The neighborhood of node v ; that is, the set of nodes that form edges with v
d_{ij}	The length of the shortest path, namely distance, between v_i and v_j
$D(G)$	The diameter of a graph G
$E(G)$	The edge density of a graph G
$\langle k \rangle$	The average degree of a network
C_i	The clustering coefficient of a node v_i
C	The clustering coefficient of a network
S	The measure of ‘small-world-ness’ of a network
L	The characteristic path length of a network
r	The assortativity of an undirected network
Q	The measure to evaluate the goodness of a community partition of a network
N_{C_x}	The number of ways a set of x objects can be selected from a pool of size N
p, q	Probability
$k(\cdot)$	The KC-complexity
F	Fitness landscape
P_{local}	The portion of local interactions used in DPE-Nets
μ	The mixing parameter for community structure
$\Lambda_i(t)$	The fitness value of node v_i at time t
T	Takeover time
$E_i[T]$	The empirical estimation of the expected takeover time given that the initial best individual is located in node v_i

$E[T]$	The overall empirically estimated expected takeover
t	The number of generations
t_{max}	Maximum number of generations
β	The probability to rewired a link in a small world network
Γ	The Gamma function