

## Chapter 8

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## Appendix A

# Parameter dependence of jDE

Section 3.4.2.6 concluded that a disadvantage of the *jDE* algorithm of Brest *et al.* [2009] is that it contains 16 parameters which may have to be fine-tuned for optimal results. This appendix empirically shows that *jDE* is sensitive to at least two of these parameters.

An experiment was designed to determine how various combinations of values for  $\tau_3$  and  $\tau_5$  affect the offline error of *jDE*. The first parameter,  $\tau_3$ , is the age that must be reached by the best individual in a sub-population before the sub-population may be reinitialised. The second parameter,  $\tau_5$ , is the age that must be reached by an individual in a sub-population before the individual may be reinitialised (refer to Section 3.4.2.3). Brest *et al.* [2009] suggested that  $\tau_3 = 30$  and  $\tau_5 = 25$  be used as defaults.

Four benchmark instances were utilised in these experiments: GDBG function  $F_3$  using change periods of 5 000 and 100 000 function evaluations, and GDBG  $F_5$  using change periods of 5 000 and 100 000 function evaluations. Change type  $T_1$  was used in 5 dimensions for all four environments. All the combinations of values for parameters  $\tau_3$  and  $\tau_5$ , which were increased in increments of 5 from 5 to 50, were evaluated. Results were averaged over 30 repeats of each of the experiments.

Figures A.1 to A.4 give the offline errors of *jDE* on  $F_3$  with a change period of 5 000,  $F_3$  with a change period of 100 000,  $F_5$  with a change period of 5 000, and  $F_5$  with a change period of 100 000, respectively. The settings for  $\tau_3$  and  $\tau_5$  had a large impact on the offline error, especially when using a change period of 5 000.

The optimal settings for  $\tau_3$  and  $\tau_5$  on  $F_3$  with a change period of 5 000 were found to

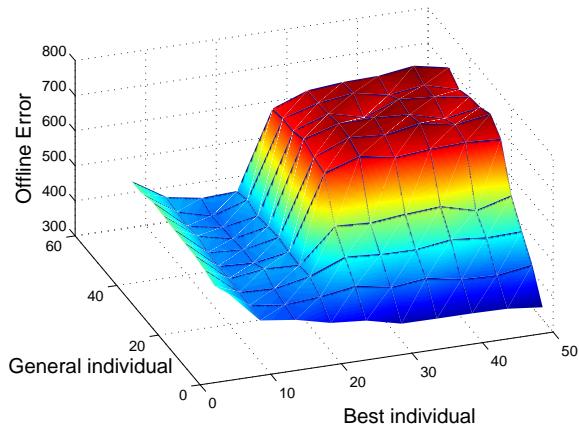


Figure A.1: Offline errors of *jDE* on the GDBG function  $F_3$  using change type  $T_1$  in 5 dimensions with a change period of 5 000 function evaluations for various combinations of settings for the parameters  $\tau_3$  and  $\tau_5$ .

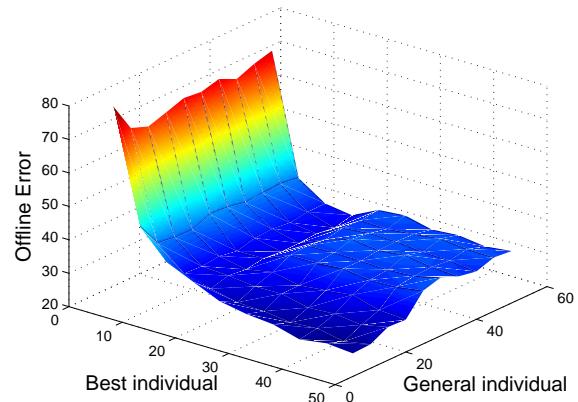


Figure A.2: Offline errors of *jDE* on the GDBG function  $F_3$  using change type  $T_1$  in 5 dimensions with a change period of 100 000 function evaluations for various combinations of settings for the parameters  $\tau_3$  and  $\tau_5$ .

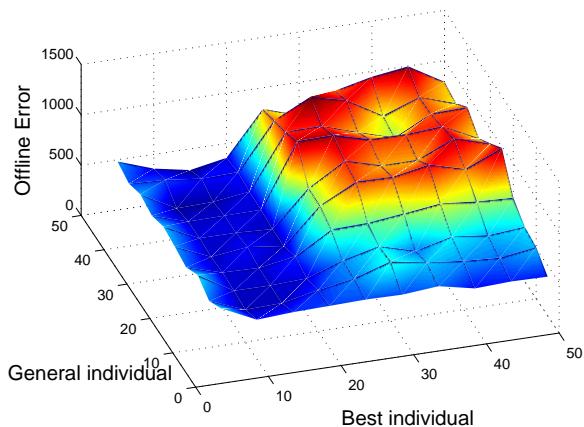


Figure A.3: Offline errors of *jDE* on the GDBG function  $F_5$  using change type  $T_1$  in 5 dimensions with a change period of 5 000 function evaluations for various combinations of settings for the parameters  $\tau_3$  and  $\tau_5$ .

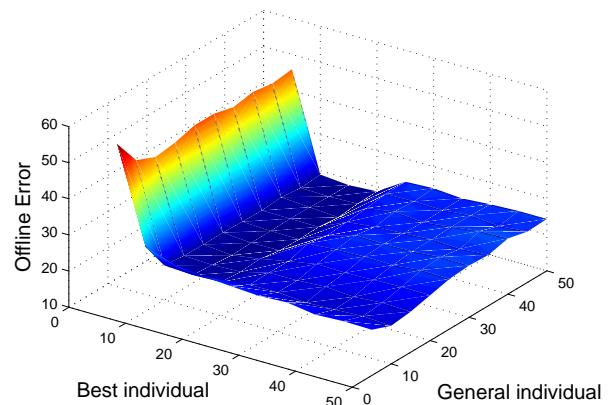


Figure A.4: Offline errors of *jDE* on the GDBG function  $F_5$  using change type  $T_1$  in 5 dimensions with a change period of 100 000 function evaluations for various combinations of settings for the parameters  $\tau_3$  and  $\tau_5$ .

be  $\tau_3 = 50$  and  $\tau_5 = 5$ . The values  $\tau_3 = 15$  and  $\tau_5 = 50$  were found to be the optimal settings on  $F_3$  with a change period of 100 000. The optimal settings for  $\tau_3$  and  $\tau_5$  on  $F_5$  with a change period of 5 000 were found to be  $\tau_3 = 45$  and  $\tau_5 = 10$ . The optimal settings for  $\tau_3$  and  $\tau_5$  on  $F_5$  with a change period of 100 000 were found to be  $\tau_3 = 20$  and  $\tau_5 = 40$ . The average offline errors produced by the optimal settings were found to be statistically significantly better than the average offline errors produced by the default settings in each of the four environments. *jDE* is thus clearly sensitive to values of the parameters  $\tau_3$  and  $\tau_5$ .

## Appendix B

# Additional Results - Chapter 4

This appendix contains results that were omitted from Chapter 4 due to space constraints. Tables B.1 and B.2 give the performance analysis of CDE compared to CPE on variations of the standard set of environments. Tables B.3 and B.4 give the performance analysis of CDE compared to RMC. The comparative performance analysis of CDE and CjDE is given in Tables B.5 and B.6.













## Appendix C

# Additional Results - Chapter 5

This appendix contains results that were omitted from Chapter 5 due to space constraints. Table C.1 and gives the performance analysis of CDE compared to DynDE on the  $n_p$  standard set of environments. CDE and DynDE used equal numbers of sub-populations as numbers of peaks. Table C.2 gives the performance analysis of DynDE10 compared to DynDE on the  $n_p$  standard set of environments. The comparative performance analysis on variations of the standard set of DynPopDE versus DynDE is given in Tables C.3 and C.4.

Table C.1: CDE vs DynDE performance analysis on the  $n_p$  standard set

$C_p$		100	500	1000	5000	10000	25000	50000	100000	Total	
Set.	Max	5 Dimensions									
$n_p$	5	(2)	↑0 ↓0	↑0 ↓0	↑1 ↓0	↑1 ↓0	↑1 ↓0	↑0 ↓0	↑0 ↓0	↑4 ↓0	
10	(2)	↑0 ↓0	↑1 ↓0	↑0 ↓0	↑1 ↓0	↑2 ↓0	↑1 ↓0	↑2 ↓0	↑2 ↓0	↑9 ↓0	
25	(2)	↑0 ↓0	↑0 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑12 ↓0	
50	(2)	↑0 ↓0	↑0 ↓0	↑0 ↓1	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑10 ↓1	
100	(2)	↑0 ↓0	↑0 ↓0	↑0 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑10 ↓0	
200	(2)	↑0 ↓0	↑1 ↓0	↑0 ↓0	↑1 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑10 ↓0	
C	(6)	↑0 ↓0	↑2 ↓0	↑2 ↓0	↑5 ↓0	↑6 ↓0	↑5 ↓0	↑5 ↓0	↑5 ↓0	↑30 ↓0	
S	(6)	↑0 ↓0	↑0 ↓0	↑1 ↓1	↑4 ↓0	↑5 ↓0	↑5 ↓0	↑5 ↓0	↑5 ↓0	↑25 ↓1	
All	(12)	↑0 ↓0	↑2 ↓0	↑3 ↓1	↑9 ↓0	↑11 ↓0	↑10 ↓0	↑10 ↓0	↑10 ↓0	↑55 ↓1	
Set.	Max	10 Dimensions									
$n_p$	5	(2)	↑1 ↓0	↑0 ↓0	↑0 ↓1	↑0 ↓0	↑0 ↓1	↑0 ↓1	↑0 ↓0	↑1 ↓3	
10	(2)	↑0 ↓0	↑1 ↓1	↑1 ↓1	↑0 ↓0	↑0 ↓0	↑0 ↓1	↑0 ↓1	↑2 ↓4		
25	(2)	↑1 ↓0	↑0 ↓0	↑1 ↓1	↑1 ↓0	↑1 ↓1	↑1 ↓1	↑0 ↓1	↑5 ↓5		
50	(2)	↑0 ↓0	↑0 ↓0	↑0 ↓0	↑1 ↓1	↑1 ↓1	↑1 ↓1	↑1 ↓1	↑4 ↓5		
100	(2)	↑0 ↓0	↑0 ↓0	↑0 ↓0	↑1 ↓1	↑1 ↓1	↑1 ↓1	↑1 ↓1	↑5 ↓5		
200	(2)	↑0 ↓0	↑0 ↓0	↑0 ↓0	↑0 ↓1	↑1 ↓1	↑1 ↓1	↑1 ↓1	↑4 ↓5		
C	(6)	↑1 ↓0	↑1 ↓0	↑2 ↓0	↑3 ↓0	↑4 ↓0	↑4 ↓1	↑3 ↓0	↑2 ↓1	↑20 ↓2	
S	(6)	↑1 ↓0	↑0 ↓1	↑0 ↓3	↑0 ↓3	↑0 ↓4	↑0 ↓4	↑0 ↓6	↑0 ↓4	↑1 ↓25	
All	(12)	↑2 ↓0	↑1 ↓1	↑2 ↓3	↑3 ↓3	↑4 ↓4	↑4 ↓5	↑3 ↓6	↑2 ↓5	↑21 ↓27	
Set.	Max	25 Dimensions									
$n_p$	5	(2)	↑0 ↓0	↑1 ↓0	↑2 ↓0	↑1 ↓0	↑2 ↓0	↑0 ↓0	↑1 ↓0	↑7 ↓0	
10	(2)	↑0 ↓0	↑1 ↓0	↑1 ↓0	↑1 ↓0	↑2 ↓0	↑1 ↓0	↑1 ↓0	↑0 ↓0	↑7 ↓0	
25	(2)	↑0 ↓0	↑0 ↓0	↑1 ↓1	↑2 ↓0	↑1 ↓0	↑1 ↓0	↑1 ↓0	↑7 ↓1		
50	(2)	↑1 ↓0	↑0 ↓0	↑0 ↓0	↑1 ↓0	↑1 ↓0	↑1 ↓1	↑1 ↓0	↑6 ↓1		
100	(2)	↑0 ↓0	↑0 ↓0	↑0 ↓0	↑1 ↓1	↑1 ↓1	↑1 ↓1	↑1 ↓1	↑5 ↓4		
200	(2)	↑0 ↓0	↑0 ↓1	↑0 ↓1	↑0 ↓2	↑1 ↓1	↑1 ↓1	↑1 ↓0	↑1 ↓7		
C	(6)	↑0 ↓0	↑2 ↓1	↑3 ↓0	↑5 ↓1	↑6 ↓0	↑5 ↓0	↑4 ↓0	↑30 ↓2		
S	(6)	↑1 ↓0	↑0 ↓0	↑1 ↓2	↑1 ↓2	↑2 ↓2	↑0 ↓3	↑0 ↓1	↑1 ↓11		
All	(12)	↑1 ↓0	↑2 ↓1	↑4 ↓2	↑6 ↓3	↑8 ↓2	↑5 ↓3	↑5 ↓1	↑5 ↓1	↑36 ↓13	
Set.	Max	50 Dimensions									
$n_p$	5	(2)	↑0 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑1 ↓0	↑1 ↓0	↑12 ↓0	
10	(2)	↑0 ↓0	↑1 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑13 ↓0	
25	(2)	↑0 ↓0	↑0 ↓0	↑1 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑11 ↓0	
50	(2)	↑0 ↓0	↑1 ↓0	↑0 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑11 ↓0	
100	(2)	↑0 ↓0	↑0 ↓0	↑0 ↓0	↑1 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑9 ↓0	
200	(2)	↑0 ↓0	↑0 ↓0	↑0 ↓0	↑0 ↓1	↑1 ↓1	↑1 ↓0	↑2 ↓0	↑2 ↓0	↑6 ↓3	
C	(6)	↑0 ↓0	↑3 ↓0	↑3 ↓0	↑5 ↓1	↑6 ↓0	↑5 ↓0	↑5 ↓0	↑5 ↓0	↑33 ↓1	
S	(6)	↑0 ↓0	↑1 ↓0	↑2 ↓0	↑4 ↓1	↑5 ↓1	↑5 ↓0	↑6 ↓0	↑6 ↓0	↑29 ↓2	
All	(12)	↑0 ↓0	↑4 ↓0	↑5 ↓0	↑9 ↓2	↑11 ↓1	↑11 ↓0	↑11 ↓0	↑11 ↓0	↑62 ↓3	
Set.	Max	100 Dimensions									
$n_p$	5	(2)	↑1 ↓0	↑1 ↓0	↑1 ↓0	↑1 ↓0	↑1 ↓0	↑0 ↓0	↑0 ↓0	↑6 ↓0	
10	(2)	↑0 ↓1	↑2 ↓0	↑2 ↓0	↑1 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑13 ↓1	
25	(2)	↑0 ↓0	↑0 ↓0	↑1 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑11 ↓0	
50	(2)	↑0 ↓0	↑0 ↓0	↑0 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑10 ↓0	
100	(2)	↑0 ↓0	↑0 ↓0	↑0 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑10 ↓0	
200	(2)	↑0 ↓0	↑0 ↓0	↑0 ↓0	↑0 ↓1	↑1 ↓0	↑2 ↓0	↑2 ↓0	↑2 ↓0	↑7 ↓2	
C	(6)	↑1 ↓0	↑2 ↓0	↑2 ↓0	↑5 ↓1	↑6 ↓0	↑6 ↓0	↑5 ↓0	↑5 ↓0	↑32 ↓1	
S	(6)	↑0 ↓1	↑1 ↓0	↑2 ↓0	↑3 ↓1	↑4 ↓0	↑5 ↓0	↑5 ↓0	↑5 ↓0	↑25 ↓2	
All	(12)	↑1 ↓1	↑3 ↓0	↑4 ↓0	↑8 ↓2	↑10 ↓0	↑11 ↓0	↑10 ↓0	↑10 ↓0	↑57 ↓3	
Set.	Max	All Dimensions									
$n_p$	5	(10)	↑2 ↓0	↑4 ↓0	↑6 ↓1	↑5 ↓0	↑6 ↓0	↑4 ↓1	↑1 ↓1	↑2 ↓0	↑30 ↓3
10	(10)	↑0 ↓1	↑6 ↓1	↑6 ↓1	↑5 ↓0	↑8 ↓0	↑6 ↓0	↑7 ↓1	↑6 ↓1	↑44 ↓5	
25	(10)	↑1 ↓0	↑0 ↓0	↑6 ↓2	↑9 ↓0	↑8 ↓1	↑8 ↓1	↑7 ↓1	↑7 ↓1	↑46 ↓6	
50	(10)	↑1 ↓0	↑1 ↓0	↑0 ↓1	↑8 ↓1	↑8 ↓1	↑8 ↓2	↑8 ↓1	↑7 ↓1	↑41 ↓7	
100	(10)	↑0 ↓0	↑0 ↓0	↑0 ↓0	↑7 ↓2	↑8 ↓2	↑8 ↓2	↑8 ↓2	↑8 ↓1	↑39 ↓9	
200	(10)	↑0 ↓0	↑1 ↓1	↑0 ↓1	↑1 ↓7	↑6 ↓3	↑7 ↓2	↑8 ↓1	↑8 ↓2	↑31 ↓17	
C	(30)	↑2 ↓0	↑10 ↓1	↑12 ↓0	↑23 ↓3	↑28 ↓0	↑26 ↓1	↑23 ↓0	↑21 ↓1	↑145 ↓6	
S	(30)	↑2 ↓1	↑2 ↓1	↑6 ↓6	↑12 ↓7	↑16 ↓7	↑15 ↓7	↑16 ↓7	↑17 ↓5	↑86 ↓41	
All	(60)	↑4 ↓1	↑12 ↓2	↑18 ↓6	↑35 ↓10	↑44 ↓7	↑41 ↓8	↑39 ↓7	↑38 ↓6	↑231 ↓47	







## Appendix D

# Additional Results - Chapter 6

This appendix contains results that were omitted from Chapter 6 due to space constraints. Tables D.1 and D.2 give the performance analysis of jSA2Ran compared to DynDE on variations of the standard set of environments. Tables D.3 and D.4 give the performance analysis of SABrNorRes compared to DynDE on variations of the standard set of environments. The comparative performance analysis on variations of the standard set of SACDE versus DynDE is given in Tables D.5 and D.6. Tables D.7 and D.8 give the performance analysis of SADynPopDE compared to CDE on variations of the standard set of environments. Tables D.9 and D.10 give the performance analysis of SADynPopDE compared to SACDE on variations of the standard set of environments. The comparative performance analysis on the  $n_p$  standard set of DynPopDE versus SACDE is given in Table D.11. Table D.12 gives the performance analysis of SACDE compared to CDE on the  $n_p(t)$  standard set of environments. The comparative performance analysis on the  $n_p(t)$  standard set of SADynPopDE versus SACDE is given in Table D.13.



























## Appendix E

### List of Symbols

$a$	general counter
$b$	general counter
$c$	change counter
$\vec{c}_p$	change in $p$ -th peak location
$\vec{d}$	average location of all individuals
$d_j$	$j$ -th component of vector $\vec{d}$
$f_{description}$	underlying benchmark function
$f_p$	$p$ -th peak / underlying benchmark function
$f_{p,opti}$	optimum value of the $p$ -th underlying benchmark function
$g$	generation counter
$h_p$	height of $p$ -th peak
$i$	individual index
$j$	dimension / component index
$j_{rand}$	randomly selected index
$k$	sub-population index
$\vec{l}_F$	location of the global optimum of dynamic function $F$
$\vec{l}_p$	location of optimum of function $f_p$
$l_{p,j}$	$j$ -th component of location of optimum of function $f_p$
$n_c$	total number of changes in a dynamic environment
$n_d$	number of dimensions

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$n_{excess}$	threshold of number of free swarms
$n_{exp}$	number of experimental environments
$n_{free}$	number of free swarms
$n_g$	number of generations
$n_I$	total number of individuals in population including sub-populations
$n_{I,k}$	number of individuals in $k$ -th sub-population
$n_k$	number of sub-populations
$n_p$	number of peaks
$n_s$	number of samples
$n_t$	total number of function evaluations
$\vec{o}$	vector used in GDBG
$p$	peak / underlying function index
$q$	GDBG control parameter index
$r$	random number
$\vec{r}$	random vector
$r_j$	random number associated with dimension $j$
$r_{brown}$	Brownian radius
$r_{dev}$	deviation from which $r_{brown}$ is selected
$r_{excl}$	exclusion radius
$r_{conv}$	convergence radius
$r_{pop,k}$	population radius of of $k$ -th sub-population
$s$	GDBG selected dimensions
$t$	time, generation counter
$\vec{u}_i$	$i$ -th DE trial vector
$u_{i,j}$	$j$ -th component of $i$ -th trial vector
$\vec{v}_i$	$i$ -th DE mutant vector
$v_{i,j}$	$j$ -th component of $i$ -th mutant vector
$w_p$	width of $p$ -th peak
$\vec{x}^*$	global optimum
$\vec{x}_i$	$i$ -th individual in the population

$\vec{x}_{i,k}$	$i$ -th individual in the $k$ -th population
$x_{i,j}$	$j$ -th component of $i$ -th individual
$\vec{x}_{best}$	best individual in the population $P_x$ since the last change in the environment
$\vec{x}_{best}(g)$	best individual in the population $P_x$ in generation $g$
$\vec{x}_{best,k}$	best individual in sub-population $P_k$ since the last change in the environment
$\vec{x}_{brown}$	Brownian individual
$\vec{y}_i$	personal best of $i$ -th individual
$\vec{y}_i$	global best
$\vec{z}$	general individual
$A_{i,k}$	age of $i$ -th individual in $k$ -th sub-population
$B$	basis function in MPB
$C(a, b)$	random number from Cauchy distribution with median $a$ and scale value $b$
$Cr$	crossover factor
$Cr_i$	crossover factor associated with $i$ -th individual
$Cr_{new_i}$	new crossover factor associated with $i$ -th individual
$C_s$	change severity
$Ct$	change type
$Cp$	change period
$D$	diversity
$Det$	change detection strategy
$D_{AP}$	average diversity per sub-population
$E_{BC}(\vec{x}_i(t), c)$	error of $\vec{x}_i$ immediately before the $c$ -th change in the environment
$F$	function to be optimised
$F_{opti}$	global optimum of function $F$
$\mathcal{F}$	scale factor
$\mathcal{F}_i$	scale factor associated with $i$ -th individual
$\mathcal{F}_{new_i}$	new scale factor associated with $i$ -th individual
$\mathcal{F}_l$	lower bound of scale factor in $jDE$
$\mathcal{F}_u$	range of scale factor changes in $jDE$
$\mathcal{G}$	DE variant greediness factor

$H$	performance measure
$H_{OE,a}$	average offline errors of an algorithm on environment $a$
$L$	Longest diagonal in the search space
$M_{n_p}$	maximum number of peaks
$M_c$	maximum fraction change in the number of peaks
$N(a, b)$	random number from normal distribution with mean $a$ and deviation $b$
$P_x$	population
$P_k$	$k$ -th sub-population
$P_{ar}$	archive sub-population
$\mathbf{R}$	rotation matrix
$R_k$	relative fitness of $k$ -th sub-population
$RE$	relative error
$S$	stagnation function
$\mathcal{S}^{n_d}$	$n_d$ dimensional search space
$\mathbf{T}$	transformation matrix
$\mathcal{T}$	set of all time steps
$U(a, b)$	random number between $a$ and $b$ sampled from an uniform distribution
$V_{max,F}$	upper search range bound of function $F$
$V_{min,F}$	lower search range bound of function $F$
$V_{max,f_p}$	upper search range bound of underlying function $f_p$
$V_{min,f_p}$	lower search range bound of underlying function $f_p$
$W_{best}(g)$	function value of the best individual within a window of $\omega$ generations
$W_{worst}(g)$	function value of the worst individual within a window of $\omega$ generations
$\alpha$	method of selecting the DE base vector
$\beta$	number of DE difference vectors
$\gamma$	method of producing DE trial vectors
$\eta$	constant controlling gradient step sizes
$\lambda$	correlation in peak shifts
$\rho_1 \dots \rho_5$	parameters
$\varrho$	parameter

$\sigma_{f_p}$	stretch factor associated with $f_p$
$\varsigma$	value used in GDBG
$\tau_1 \dots \tau_{14}$	parameters
$\vec{\phi}_\Omega$	vector of GDBG control parameter $\Omega$
$\phi_{\Omega,q}$	$q$ -th component GDBG control parameter $\Omega$
$\phi_{\Omega,max}$	maximum value of the GDBG control parameter $\Omega$
$\phi_{\Omega,min}$	minimum value of the GDBG control parameter $\Omega$
$\phi_{\Omega,sev}$	severity by which the value of the $q$ -th component GDBG control parameter $\Omega$ is changed
$\varpi$	parameter
$\psi_p$	weighting factor of $p$ -th underlying function used in GDBG
$\omega$	window size
$\Omega$	GDBG control parameter
$\mathcal{P}$	performance value
$\mathcal{P}_k$	performance value of $k$ -th sub-population

## Appendix F

### List of Abbreviations

API	Average Percentage Improvement
CDE	Competing Differential Evolution
CESO	Collaborative Evolutionary-Swarm Optimisation
CPE	Competitive Population Evaluation
DE	Differential Evolution
DOP	Dynamic Optimisation Problem
DynPopDE	Dynamic Population Differential Evolution
EA	Evolutionary Algorithm
EO	Extremal Optimisation
EP	Evolutionary Programming
ES	Evolution Strategies
ESCA	Evolutionary Swarm Cooperative Algorithm
GA	Genetic Algorithm
GDBG	Generalised Dynamic Benchmark Generator
MGA	Multinational Genetic Algorithm
MMEO	Multi-Phase Multi-Individual Extremal Optimisation
MPB	Moving Peaks Benchmark
PSO	Particle Swarm Optimisation
RMC	Reinitialisation Midpoint Check
SACDE	Self-Adaptive Competing Differential Evolution

*APPENDIX F. LIST OF ABBREVIATIONS*

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SADynPopDE Self-Adaptive Dynamic Population Differential Evolution

SOS Self-Organizing Scouts

SBGA Shifting Balance Genetic Algorithm

SDE Self-adaptive Differential Evolution

SPSO Speciation-based Particle Swarm Optimisation

## Appendix G

# Derived Publications

This appendix lists the publications that have resulted from this study.

M.C. du Plessis and A.P. Engelbrecht. Improved differential evolution for dynamic optimization problems. *IEEE Congress on Evolutionary Computation*, pages 229-234. IEEE, 2008.

M.C. du Plessis and A.P. Engelbrecht. Self-adaptive competitive differential evolution for dynamic environments. *IEEE Symposium on Differential Evolution*. IEEE, 2011.

M.C. du Plessis and A.P. Engelbrecht. Using competitive population evaluation in a differential evolution algorithm for dynamic environments. *European Journal of Operational Research*, 218(1):7-20. Elsevier, 2012

M.C. du Plessis and A.P. Engelbrecht. Differential evolution for dynamic environments with unknown numbers of optima. *Journal of Global Optimization*. Springer, Available online February 7, 2012

M.C. du Plessis and A.P. Engelbrecht. Self-adaptive differential evolution for dynamic environments with fluctuating numbers of optima. *Metaheuristics for Dynamic Optimization*, E. Alba, A. Nakib, P. Siarry (eds.), Springer, to appear 2012