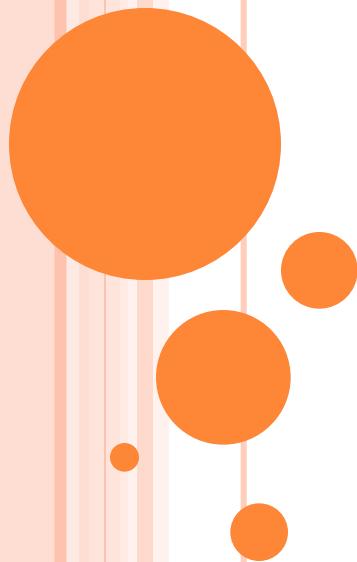


# Parameter Control Mechanisms in Differential Evolution: A Tutorial Review and Taxonomy

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# Outline

- **Introduction**
- **Proposed Taxonomy**
- **A Quick Review**
- **Research Directions**

# Differential Evolution (DE)

Each individual  $x_i$  serves as the target vector once.

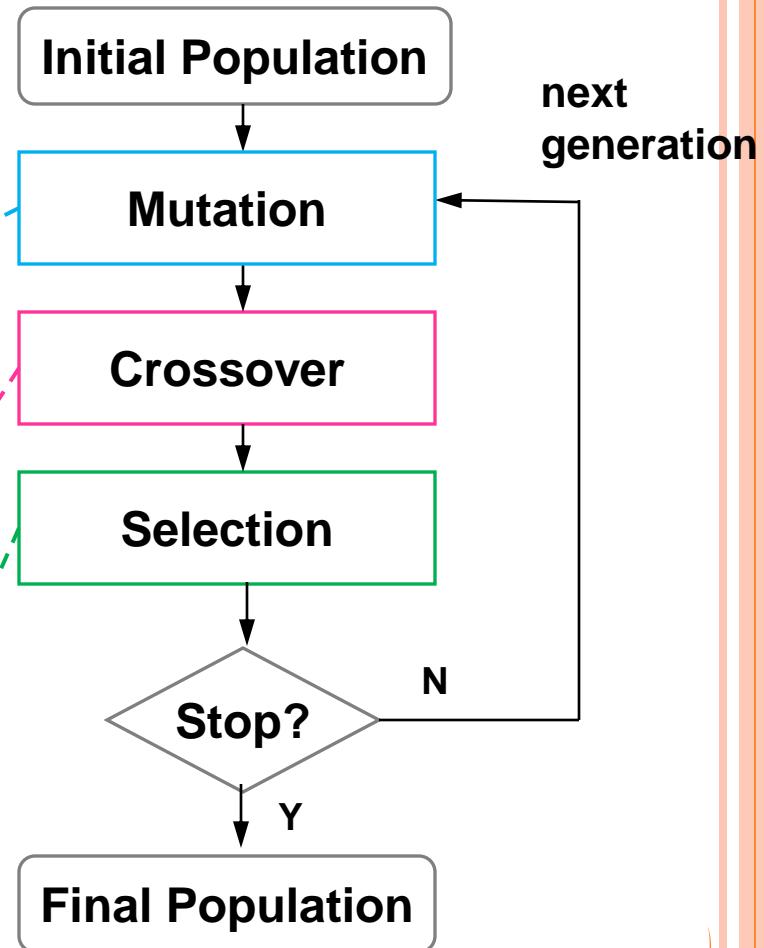
For each target vector, a mutant vector  $v_i$  is generated by

$$v_i = x_{r1} + F \cdot (x_{r2} - x_{r3})$$

A trial vector  $u_i$  is generated by

$$u_{ij} = \begin{cases} v_{ij}, & \text{if } U_j(0,1) \leq CR \vee j = j_{rnd} \\ x_{ij}, & \text{otherwise} \end{cases}$$
$$j = 1, 2, \dots, D$$

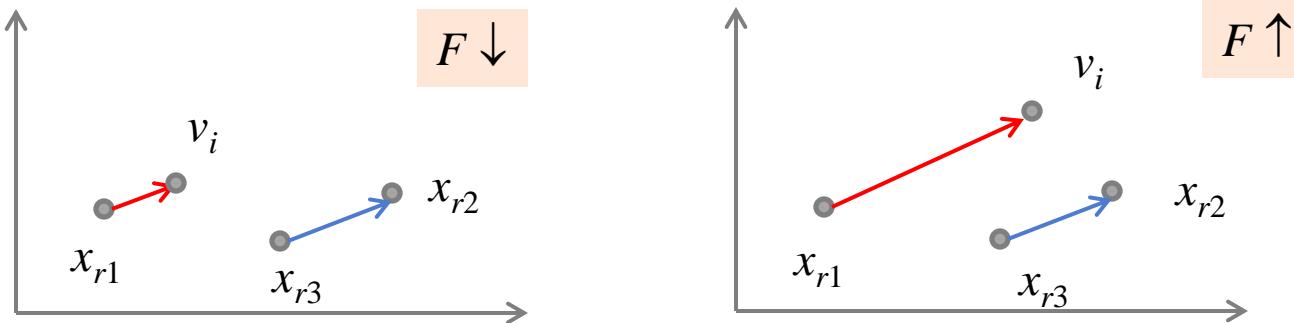
The trial vector is accepted if it is not worse than the target vector.



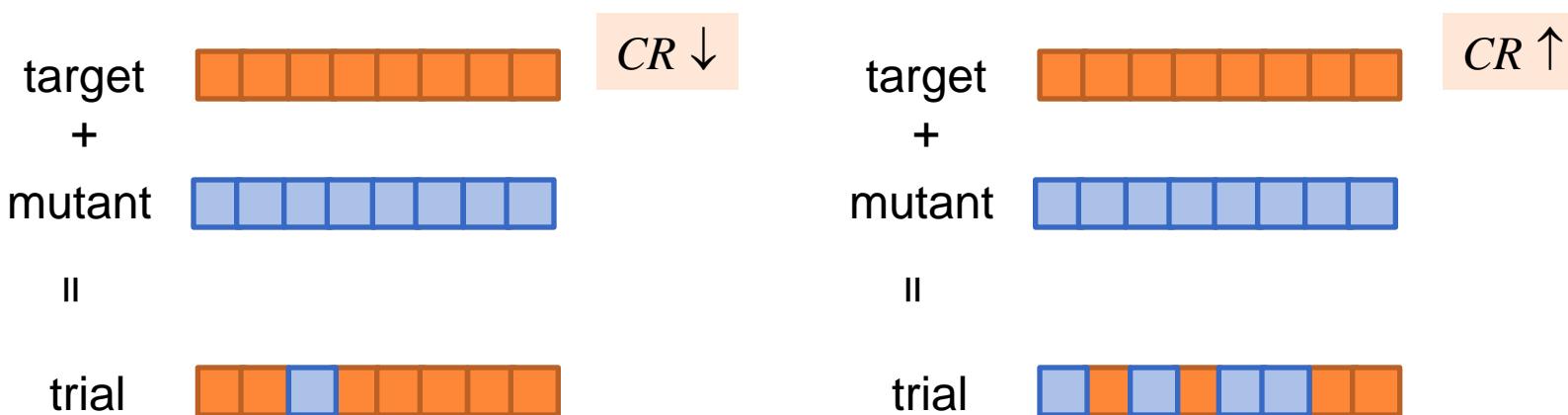
- Population size ( $NP$ )

# Parameters of DE

- Scaling Factor ( $F$ )  $v_i = x_{r1} + \textcolor{red}{F} \cdot (x_{r2} - x_{r3})$



- Crossover Rate ( $CR$ )



# Parameters of DE

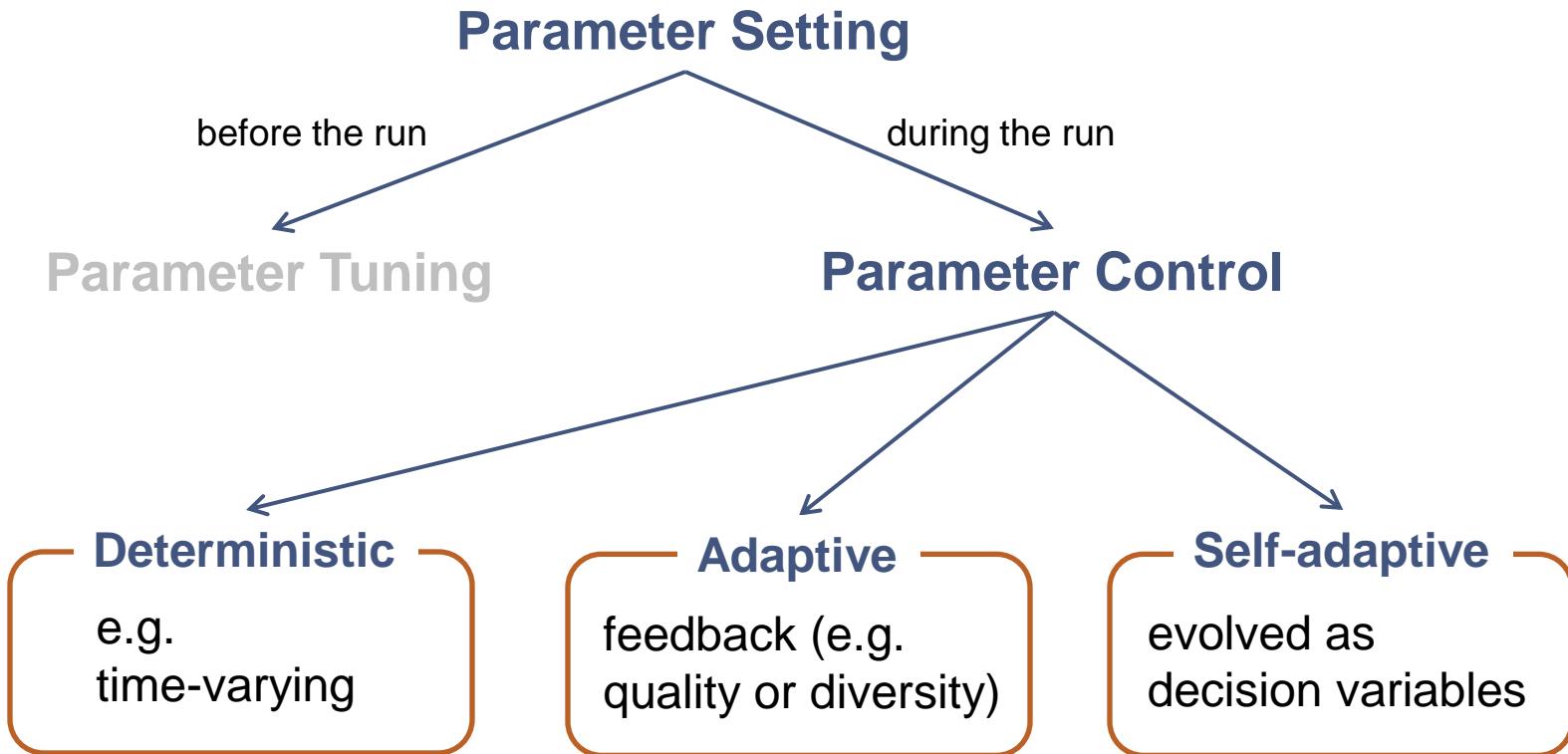
## ○ Suggestions on parameter values

F	CR	Reference
[0.4, 1.0]	0.1, 0.9	Storn & Price 1997
0.9	0.9	Liu & Lampinen 2002
	0.5	Ali & Törn 2004
0.9	0.9	Rönkkönen et al. 2005
0.5	0.5	Kaelo & Ali 2006
$\geq 0.6$	$\geq 0.6$	Zielinski et al. 2006
[0.35, 0.37]	0.5	Salman et al. 2007

# Parameters of DE

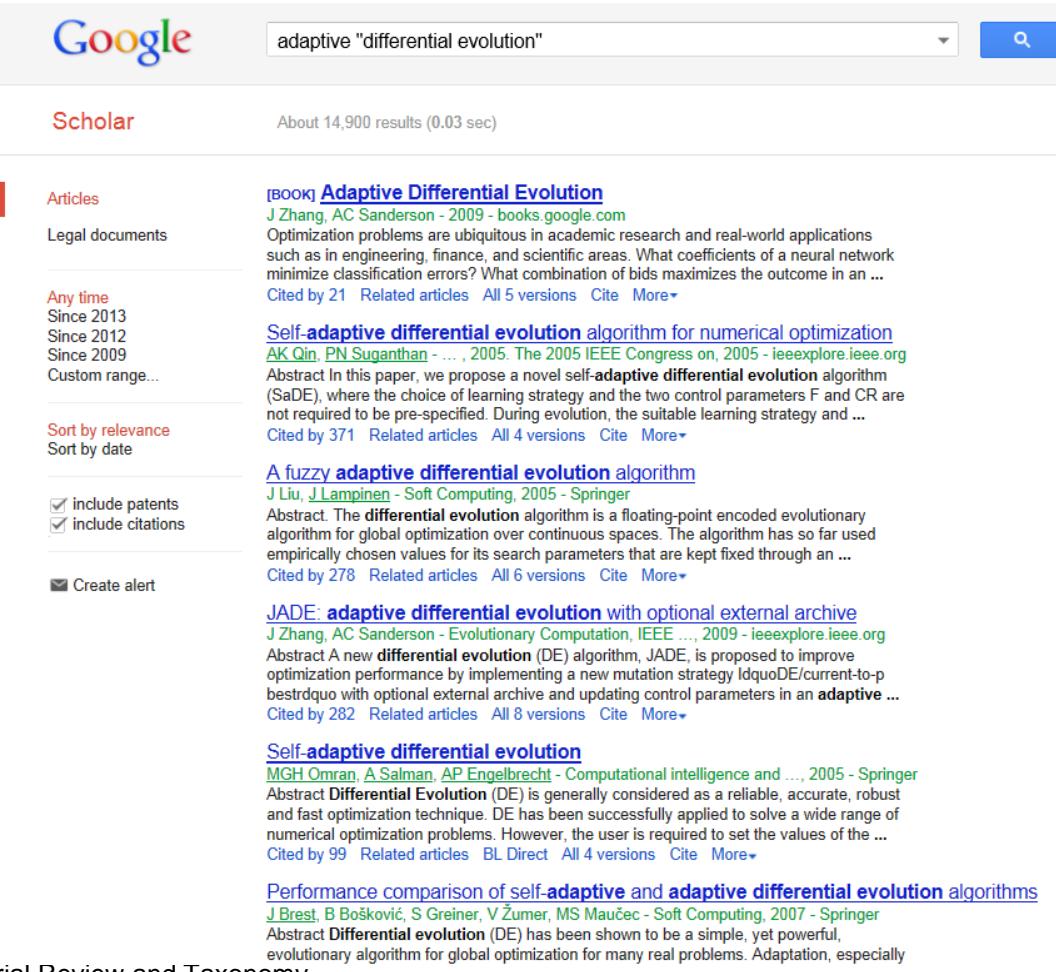
- **Different parameter values are required for different**
  - **problem instances**
  - **mutation strategies**
  - **search stages**
  - **search regions**
- **We need to determine the parameter values dynamically (online).**

# Parameter Control Paradigms



# Parameter Control Paradigms

- There are many “adaptive” or “self-adaptive” DE algorithms.



Google Scholar search results for "adaptive differential evolution". The search returned about 14,900 results in 0.03 seconds.

**Articles**

- [BOOK] Adaptive Differential Evolution**  
J Zhang, AC Sanderson - 2009 - books.google.com  
Optimization problems are ubiquitous in academic research and real-world applications such as in engineering, finance, and scientific areas. What coefficients of a neural network minimize classification errors? What combination of bids maximizes the outcome in an ...  
Cited by 21 Related articles All 5 versions Cite More▼
- Self-adaptive differential evolution algorithm for numerical optimization**  
AK Qin, PN Suganthan - ... , 2005. The 2005 IEEE Congress on, 2005 - ieeexplore.ieee.org  
Abstract In this paper, we propose a novel self-adaptive differential evolution algorithm (SaDE), where the choice of learning strategy and the two control parameters F and CR are not required to be pre-specified. During evolution, the suitable learning strategy and ...  
Cited by 371 Related articles All 4 versions Cite More▼
- A fuzzy adaptive differential evolution algorithm**  
J Liu, J Lampinen - Soft Computing, 2005 - Springer  
Abstract The differential evolution algorithm is a floating-point encoded evolutionary algorithm for global optimization over continuous spaces. The algorithm has so far used empirically chosen values for its search parameters that are kept fixed through an ...  
Cited by 278 Related articles All 6 versions Cite More▼
- JADE: adaptive differential evolution with optional external archive**  
J Zhang, AC Sanderson - Evolutionary Computation, IEEE ..., 2009 - ieeexplore.ieee.org  
Abstract A new differential evolution (DE) algorithm, JADE, is proposed to improve optimization performance by implementing a new mutation strategy IdquoDE/current-to-p-bestIdquo with optional external archive and updating control parameters in an adaptive ...  
Cited by 282 Related articles All 8 versions Cite More▼
- Self-adaptive differential evolution**  
MGH Omran, A Salman, AP Engelbrecht - Computational intelligence and ..., 2005 - Springer  
Abstract Differential Evolution (DE) is generally considered as a reliable, accurate, robust and fast optimization technique. DE has been successfully applied to solve a wide range of numerical optimization problems. However, the user is required to set the values of the ...  
Cited by 99 Related articles BL Direct All 4 versions Cite More▼
- Performance comparison of self-adaptive and adaptive differential evolution algorithms**  
J Brest, B Bošković, S Greiner, V Žumer, MS Maučec - Soft Computing, 2007 - Springer  
Abstract Differential evolution (DE) has been shown to be a simple, yet powerful, evolutionary algorithm for global optimization for many real problems. Adaptation, especially

# Proposed Taxonomy

- ## ○ 3-field notation for the DE variants

## the number of difference vectors

the vector to be mutated

## the crossover scheme

x / y / z

rand/1/bin

best/2/bin

## current-to-rand/1/bin

## rand/1/exp

## rand/2/exp

# Proposed Taxonomy

- 3-field notation for the parameter control mechanisms

x / y / z

- the number of candidate values of a parameter
  - dis (discrete) / con (continuous)
- the number of parameter values used in a single generation
  - 1 / mul (multiple) / idv (individual) / var (variable)
- information used to adjust parameter values
  - rnd (random) / pop (population) / par (parent) / idv (individual)

# Proposed Taxonomy

- We classify 23 recent studies into nine categories.

Category	Algorithms
<b>con / 1 / pop</b>	DEPD, FADE, ADEA
<b>con / mul / rnd</b>	NSDE
<b>con / mul / pop</b>	SaDE, SaNSDE, JADE, JADE2, SaJADE
<b>con / idv / rnd</b>	jDE, jDE-2, CSDE, MOSADE
<b>con / idv / pop</b>	RADE, ISADE
<b>con / idv / par</b>	SPDE, SDE, DESAP, DEMOsWA
<b>con / idv / idv</b>	SFLSDE, SspDE
<b>con / var / pop</b>	APDE
<b>dis / mul / pop</b>	DEBR

# con / 1 / pop

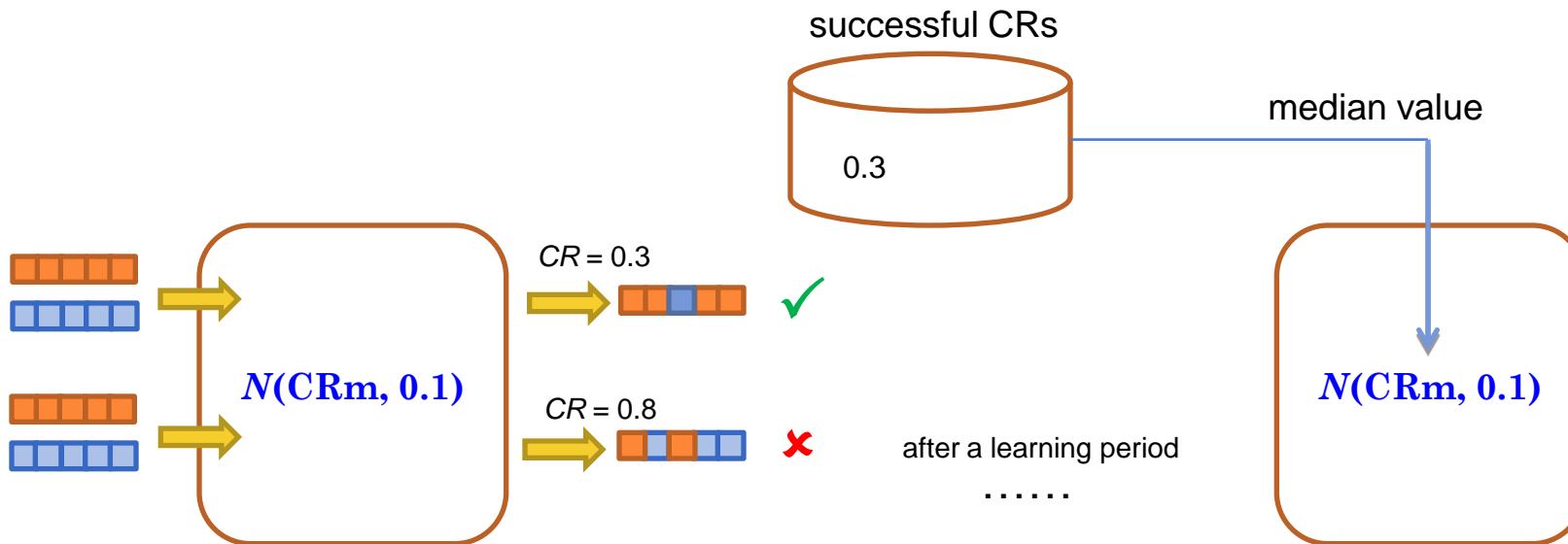
- Example: **DEPD** (Ali and Tórn, 2004)
  - Fixed **CR** value
  - Increase **F** as the difference of fitness between the best and worst individuals decreases

$$F = \begin{cases} \max\{F_{\min}, 1 - |f_{\max} / f_{\min}| \}, & \text{if } |f_{\max} / f_{\min}| < 1, \\ \max\{F_{\min}, 1 - |f_{\min} / f_{\max}| \}, & \text{otherwise.} \end{cases}$$

- Other population-based information
  - diversity (genotypic or phenotypic distance) within a generation or between generations (e.g. **FADE**)
  - distribution along the Pareto front (e.g. **ADEA**)

# con / mul / pop

- Example: **SaDE** (Qin et al. 2009)
  - Generate  $F/CR$  values by normal distribution
    - $F \sim N(0.5, 0.5)$
  - Record the successful  $CR$  values in a learning period
    - successful: the trial vector is accepted



# con / mul / pop

- Design issues
  - random distributions for generating the parameter value
    - normal / Cauchy (e.g. SaDE / **SaNSDE & JADE**)
  - learning period (*LP*)
    - $LP = 1$  /  $LP > 1$
  - calculation of distribution parameters
    - median / weighted sum (e.g. SaDE / SaNSDE & JADE)

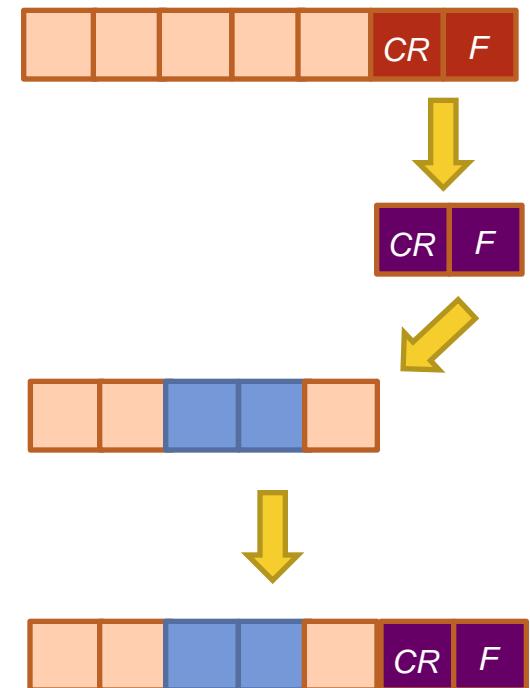
# con / idv / rnd

- Example: jDE (Brest et al. 2006)
  - Each individual records its parameter values.
  - The values undergo random perturbation probabilistically.

$$F_{i,g+1} = \begin{cases} U_1(F_{\min}, F_{\max}), & \text{if } U_2(0,1) < \tau_1, \\ F_{i,g}, & \text{otherwise.} \end{cases}$$

$$CR_{i,g+1} = \begin{cases} U_3(0,1), & \text{if } U_4(0,1) < \tau_2, \\ CR_{i,g}, & \text{otherwise.} \end{cases}$$

- Good parameter values lead to good trial vectors and survive together with the trial vectors.



# con / idv / rnd

## ○ Design issues

- random distributions for perturbation
  - uniform / Cauchy (e.g. jDE / CSDE)
- population information ( $\Rightarrow$  con / idv / pop)
  - change the parameter values only for low-quality individuals (e.g. RADE)
  - lower the parameter values for high-quality individuals (e.g. ISADE)
- individual information ( $\Rightarrow$  con / idv / idv)
  - use local search to enhance the values (e.g. SFLSDE)
  - record the history of the use of parameter values for each individual (e.g. SspDE)

# con / idv / par

- Example: **SPDE** (Abbass 2002)
  - Each individual records its parameter values.
  - Parameter values evolve as the decision variable values evolve.



$$CR_i = CR_{r1} + N(0,1) \cdot (CR_{r2} - CR_{r3})$$

- Design issues
  - the way to calculate the new parameter values based on parents' values (e.g. **DEMOwSA**)

$$CR_i = \frac{CR_i + CR_{r1} + CR_{r2} + CR_{r3}}{4} \cdot e^{\tau \cdot N(0,1)}$$

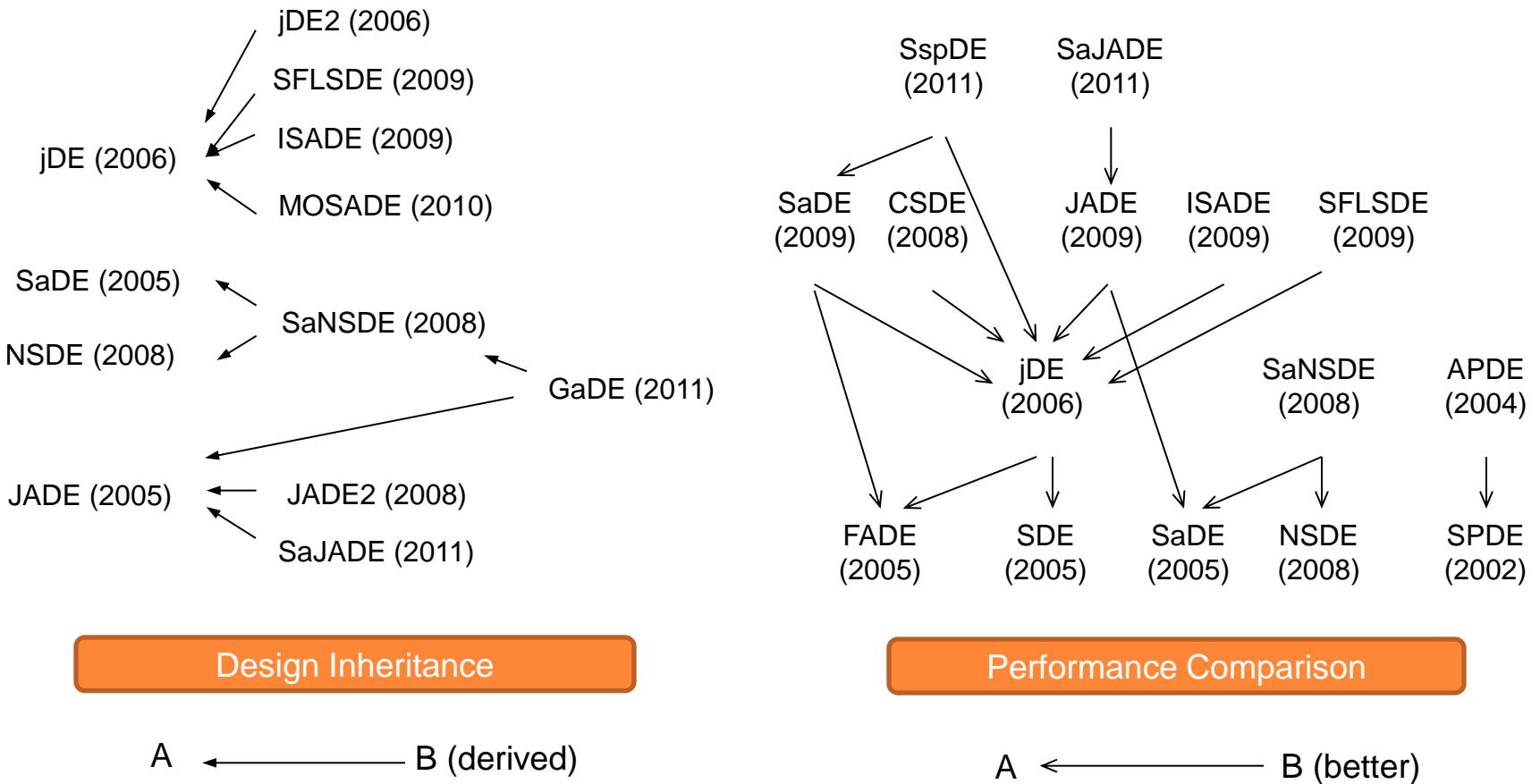
# con / var / pop

- Example: APDE (Zaharie and Petcu 2004)
  - Parameter values are associated with variables.
  - Relationships between the parameter values and the variance of values of decision variables are investigated.
  - Values of  $CR$  and  $F$  are adjusted alternately.

$$CR_i = \begin{cases} -(F_i^2 N - 1) + \sqrt{(F_i^2 N - 1)^2 - N(1 - c_i)}, & \text{if } c_i \geq 1 \\ CR_{\min} & \text{otherwise} \end{cases}$$

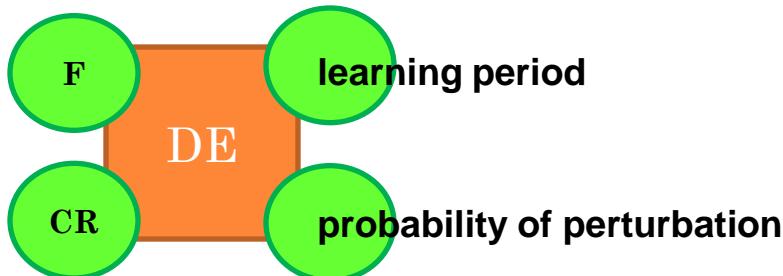
$$c_i(g+1) = \gamma \frac{Var(x^i(g))Var(f(g))}{Var(x^i(g+1))Var(f(g+1))}$$
$$Var(f(g)) = \frac{1}{M} \sum_{j=1}^M Var(f_j(g))$$

# Some Relationships



# Research Directions

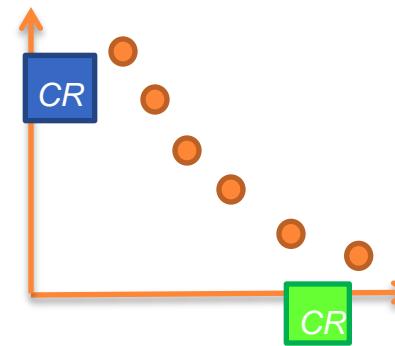
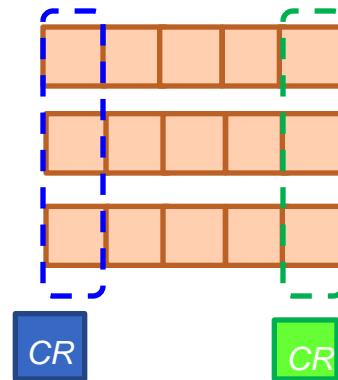
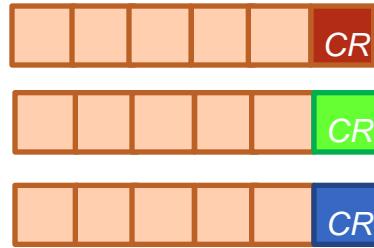
- Making the algorithm **simpler**
  - avoid extra parameters like learning period or probability.



- Considering **problem-oriented information**
  - Quality & diversity information have been used.
  - Problem information (unimodal/multimodal, separable/non-separable, etc.) has rarely been considered.
  - $\cdot/\cdot/\text{pop}$ ,  $\cdot/\cdot/\text{idv}$ , then  $\cdot/\cdot/\text{prb}$  ?  
⇒ LMDE (Takahama and Sakai 2012)

# Research Directions

- Adapting with respect to **multiple objectives**



• ./idv/ ·

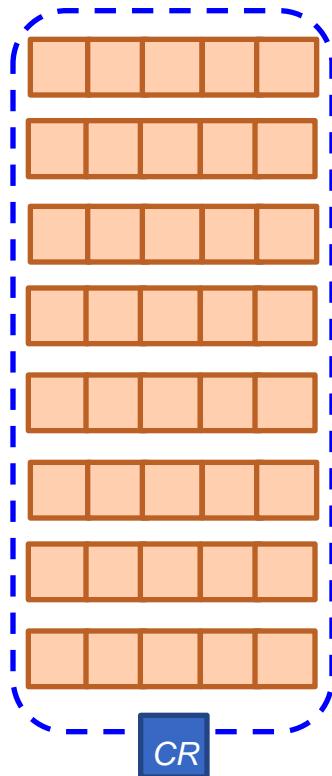
· /var/ ·,

then · /obj/ · ?

⇒ OW-MOSaDE (Huang et al. 2009)

# Research Directions

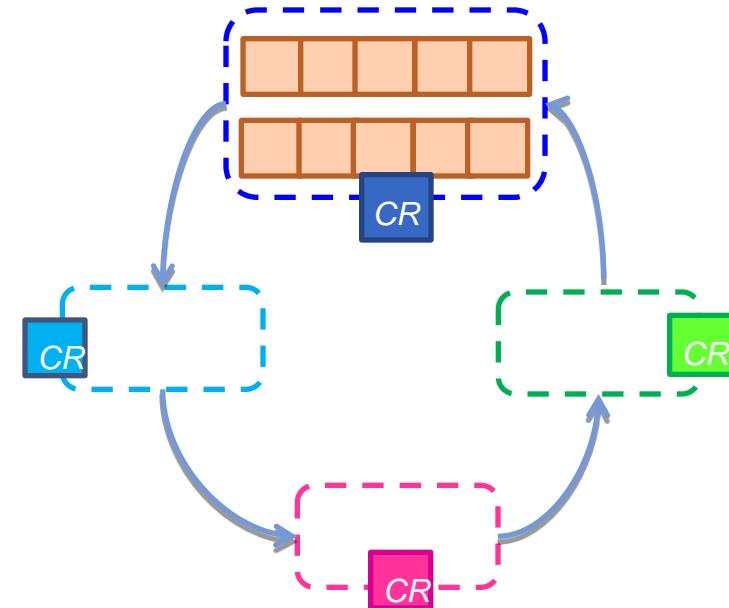
- Doing parameter control through **distributed DE**



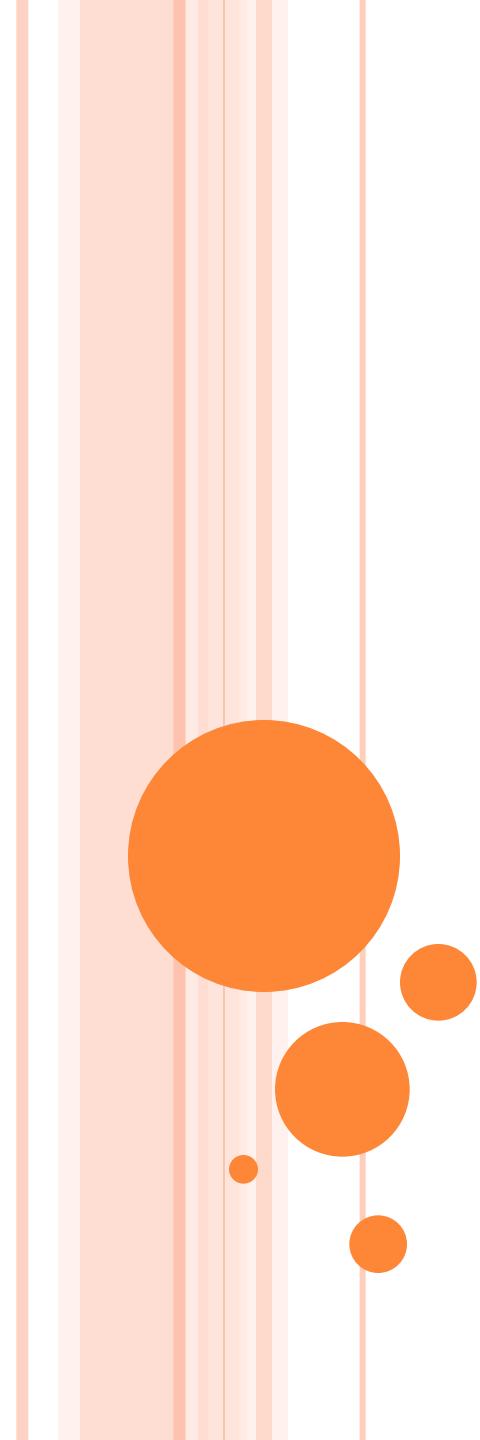
· / 1 / ·



· / idv / · ,



then · / sub-pop / · ?  
⇒ **FACPDE** (Weber et al. 2010)



**Thank you very much  
for your attention!**