Work 01: Evolutionary computation

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Google Scholar: *https://scholar.google.com/citations?user=0X7VkC4AAAAJ&hl=pt-PT*
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Work 01: 2 tasks

- ✓ Part 01: *Theoretical*

- ✓ Part 02: *Practical*

Leandro dos Santos Coelho

Part 01: *Theoretical*

General

❶ What is evolutionary computation?

Genetic algorithms

❷ Explain some basic concepts and terms related to genetic algorithm with binary representation i.e. population, chromosome, gene, allele, fitness function, and genetic operators

❸ Compare the single-point and two-point crossover in a genetic algorithm with binary representation.

❹ What are some potentialities and disadvantages of genetic algorithms?

Differential evolution

❻ Describe the crossover (recombination) operation in a classical differential evolution approach.

❼ Describe the mutation operation in a classical differential evolution approach.

Part 01: *Theoretical*

Some references in Portuguese

Introdução a computação evolutiva, UNICAMP, Fernando Von Zuben
ftp://ftp.dca.fee.unicamp.br/pub/docs/vonzuben/ea072_2s11/topico2_EA072_2s2011.pdf

Fundamentos de algoritmos evolutivos, USP, Paulo P.R. Gabriel e Alexandre C. B. Delbem
http://conteudo.icmc.usp.br/CMS/Arquivos/arquivos_enviados/BIBLIOTECA_113_ND_75.pdf

Evolução diferencial – introdução e conceitos básicos, UNICAMP, Lwvy Boccato et al.
ftp://vm1-dca.fee.unicamp.br/pub/docs/vonzuben/ia707_1s11/notas_de_aula/topico12_IA707_1s11.pdf

Part 01: *Theoretical*

❶ **Complete the following tables** with the steps of a genetic algorithm (GA) during a evolutionary cycle.

a) Generation of the **initial population** of solutions and **evaluation of objective function**

Set the initial generations counter: ***generation* = 0**

Member of population	Genotype (binary representation) Base 2			Phenotype (floating point representation) Base 10			(maximization) objective function, f
	g_1	g_2	g_3	x_1	x_2	x_3	$f = x_1+x_2+x_3$
1	001.11	001.10	010.00	1.750	1.500	2.000	5.250
2		000.01		0.125		1.875	
3	001.00	010.01	000.11				
4	110.01	010.11					
Best member							

Part 01: *Theoretical*

b) Apply the **crossover operation** after selection using roulette selection

Selected the same cut point in the 3rd position (left to right)

Example: In the member 1, g_1 with 001.11 has cut in 00|1.11

Selected members to match (parents)	Genotype of the offspring Base 2			Phenotype of the offspring Base 10		
	g_1'	g_2'	g_3'	x_1'	x_2'	x_3'
1': 1 and 2						
2': 1 and 2						
3': 2 and 3						
4': 2 and 3						

c) Apply the **mutation operation**

Members to apply the mutation (offspring)	Genotype of the offspring Base 2			Phenotype of the offspring Base 10		
	g_1''	g_2''	g_3''	x_1''	x_2''	x_3''
1': yes						
2': no						
3': yes						
4': no						

Part 01: *Theoretical*

d) New **population** of solutions and **evaluation of objective function**

Update the generation counter i.e. *generation* = *generation* +1 and return to Step b

Member of population	Genotype of the current population (binary representation) Base 2			Phenotype of the current population (floating point representation) Base 10			(maximization) objective function, f New
	g_1''	g_2''	g_3''	x_1''	x_2''	x_3''	$f = x_1+x_2+x_3$
1"							
2"							
3"							
4"							
Current best member							

Part 02: *Practical*

❶ **Choice 3 optimization problems** to solve using genetic algorithm and differential evolution.

❷ **Build a TABLE with results** (**30 runs**, with the SAME initial population to each run of the optimizer) related to objective function (*f*) values (min, max, mean, std) using a **genetic algorithm (GA) and differential evolution (DE)** approach. Adopt 3 different setups for each GA and DE approach to **3 optimization case studies** in the continuous domain.

```
% Matlab
>> rng(run_integer_number, 'twister') % for reproducibility in 30 runs
```

❸ **Comments the optimization results** in a report (in a *zipped* file) in terms of the quality of the results and convergence given by a **TABLE** (details in the next slide).

Maximum size of groups: 4 students

Part 02: *Practical*

❷ **Some details: Build a TABLE with results (30 runs**, with the SAME initial population to each run of the optimizer) related to objective function (*f*) values (min, max, mean, std) using a **genetic algorithm (GA) and differential evolution (DE)** approach. Adopt 3 different setups for each GA and DE approach to **3 optimization case studies** in the continuous domain.

Comment the results of optimization for the 3 case studies. Sent the zipped source code in the finished work too.

DESCRIPTION

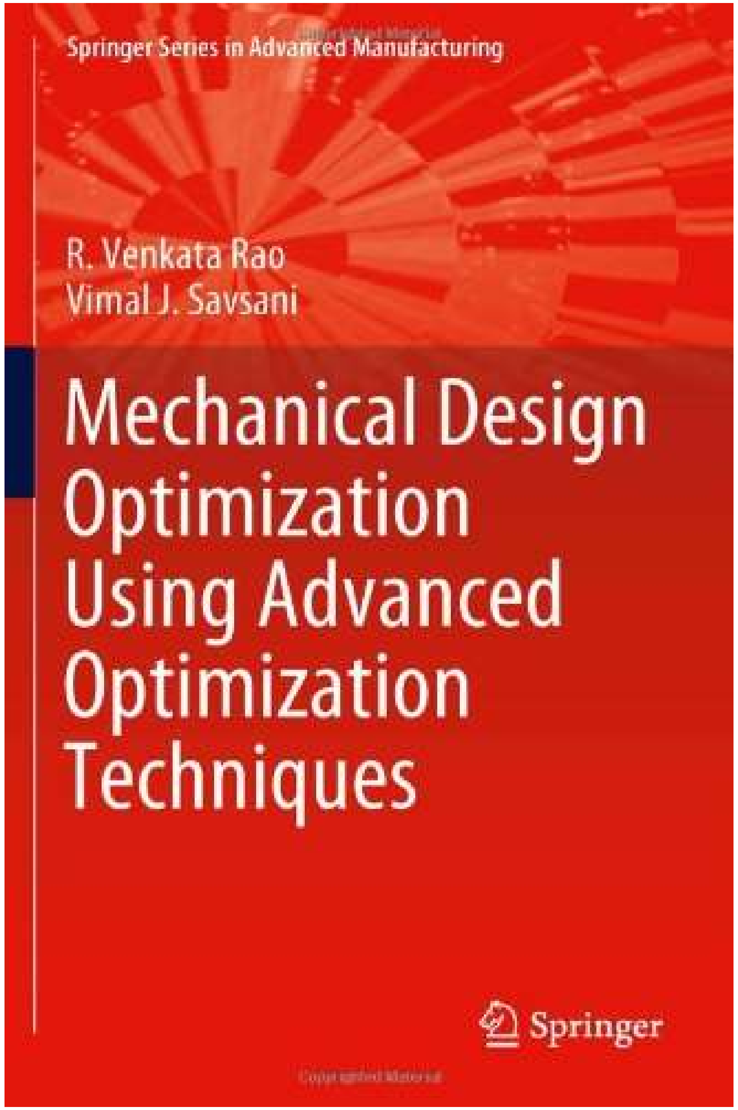
Optimization problem (minimization OR maximization): _______________
Brief description of the optimization problem (2 paragraphs and link)
Dimension of optimization problem: ___ D
Population size: ___ members
Stopping criterion: ___ generations
Number of runs: ___

TABLE

Setup	Crossover Rate	Mutation Rate	Minimum *f*	Mean *f*	Median *f*	Maximum *f*	Standard deviation, *f*
GA-1							
GA-2							
GA-3							
DE-1							
DE-2							
DE-3							
What was the best result?							

Suggestions of case studies in optimization

Sugestion 1: Mechanical design



4.3 Additional Mechanical Element Design Optimization Problems (MD) 87

4.3 Additional Mechanical Element Design Optimization Problems (MD)

Seven different mechanical element design optimization problems are presented in Chap. 2. In this chapter, thirteen more mechanical design element design optimization problems are presented. Details of these additional mechanical element design optimization problems are given as follows:

4.3.1 Example 8: Design of Pressure Vessel
4.3.2 Example 9: Design of Welded Beam
4.3.3 Example 10: Design of Tension/Compression Spring
4.3.4 Example 11: Design of a Speed Reducer
4.3.5 Example 12: Design of Stiffened Cylindrical Shell
4.3.6 Example 13: Design of Step Cone Pulley
4.3.7 Example 14: Design of Screw Jack
4.3.8 Example 15: Design of C-Clamp
4.3.9 Example 16: Design of Hydrodynamic Bearing
4.3.10 Example 17: Design of Cone Clutch
4.3.11 Example 18: Design of Cantilever Support
4.3.12 Example 19: Design of Hydraulic Cylinder
4.3.13 Example 20: Design of Planetary Gear Train

https://libgen.is/book/index.php?md5=611FEA61F6BCB661048FC05D01C78C5E

Sugestion 2: Mechanical design

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Computer-Aided Design 43 (2011) 303–315

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journal homepage: www.elsevier.com/locate/cad

Teaching–learning-based optimization: A novel method for constrained mechanical design optimization problems

R.V. Rao*, V.J. Savsani, D.P. Vakharia

Department of Mechanical Engineering, S.V. National Institute of Technology, Surat-395 007, India

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ABSTRACT

A new efficient optimization method, called 'Teaching–Learning-Based Optimization (TLBO)', is proposed in this paper for the optimization of mechanical design problems. This method works on the effect of influence of a teacher on learners. Like other nature-inspired algorithms, TLBO is also a population-based method and uses a population of solutions to proceed to the global solution. The population is considered as a group of learners or a class of learners. The process of TLBO is divided into two parts: the first part consists of the 'Teacher Phase' and the second part consists of the 'Learner Phase'. 'Teacher Phase' means learning from the teacher and 'Learner Phase' means learning by the interaction between learners. The basic philosophy of the TLBO method is explained in detail. To check the effectiveness of the method it is tested on five different constrained benchmark test functions with different characteristics, four different benchmark mechanical design problems and six mechanical design optimization problems which have real world applications. The effectiveness of the TLBO method is compared with the other population-based optimization algorithms based on the best solution, average solution, convergence rate and computational effort. Results show that TLBO is more effective and efficient than the other optimization methods for the mechanical design optimization problems considered. This novel optimization method can be easily extended to other engineering design optimization problems.

https://www.sciencedirect.com/science/article/abs/pii/S0010448510002484

Appendix B and C

B.1. Design of pressure vessel
B.2. Design of tension/compression spring
B.3. Design of welded beam design
B.4. Design of gear train
C.1. Multiple disc clutch brake design
C.2. Robot gripper
C.3. Step-cone pulley
C.4. Hydrodynamic thrust bearing design
C.5. Rolling element bearing
C.6. Belleville spring

Expert Systems With Applications 183 (2021) 115351

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Comparison of metaheuristic optimization algorithms for solving constrained mechanical design optimization problems

Shubham Gupta[a,1], Hammoudi Abderazek[b,2], Betül Sultan Yıldız[c,3], Ali Riza Yildiz[d,4,*], Seyedali Mirjalili[e,f,5], Sadiq M. Sait[g,6]

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https://www.sciencedirect.com/science/article/abs/pii/S095741742100779X

Appendix A

A.1. Compression/tension spring
A.2. Welded beam
A.3. Pressure vessel
A.4. Tubular column
A.5. Spur gear design
A.6. Step-cone pulley
A.7. Reinforced concrete beam
A.8. Piston lever

Leandro dos Santos Coelho

Sugestion 3: IEEE CEC 2011

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Benchmarks for Evaluation of Evolutionary Algorithms

We organized several competitions on benchmarking evolutionary algorithms. Recently, we also developed **several composition functions** to evaluate evolutionary algorithms. The objective of this work is explained in our Swarm Intelligence Symposium 200 and also in the CEC Invited Session / Competition pages listed below.

J. J. Liang, P. N. Suganthan and K. Deb, "Novel Composition Test Functions for Numerical Global Optimization", *IEEE Swarm Intelligence Symposium*, pp. 68-75, June 2005. Matlab codes of composition functions.

CEC'05 Special Session / Competition **on Evolutionary Real Parameter single objective optimization**
CEC'06 Special Session / Competition **on Evolutionary Constrained Real Parameter single objective optimization**
CEC'07 Special Session / Competition **on Performance Assessment of real-parameter MOEAs**
CEC'08 Special Session / Competition **on large scale single objective global optimization with bound constraints**
CEC'09 Special Session / Competition **on Dynamic Optimization (Primarily composition functions were used)**
CEC09 Special Session / Competition **on Performance Assessment of real-parameter MOEAs**
CEC10 Special Session / Competition **on large-scale single objective global optimization with bound constraints**
CEC10 Special Session / Competition **on Evolutionary Constrained Real Parameter single objective optimization**
CEC10 Special Session on Niching **Introduces novel scalable test problems:** B. Y. Qu and P. N. Suganthan, "Novel Multimodal Problems and Differential Evolution with Ensemble of Restricted Tournament Selection", *IEEE Congress on Evolutionary Computa* Barcelona, Spain, July 2010.
CEC11 Competition **on Testing Evolutionary Algorithms on Real-world Numerical Optimization Problems**
CEC2013 Special Session / Competition **on Real Parameter Single Objective Optimization**
CEC2014 Special Session / Competition **on Real Parameter Single Objective Optimization (incorporates expensive function optimization)**
CEC2014: Dynamic MOEA Benchmark Problems: Subhodip Biswas, Swagatam Das, P. N. Suganthan and C. A. C Coello, "Evolutionary Multiobjective Optimization in Dynamic Environments: A Set of Novel Benchmark Functions," Proc. CEC 2014, July, Beijing, China.

CEC2015 Special Session / Competition **on Real Parameter Single Objective Optimization (incorporates 3 scenarios)**

CEC11 Competition on Testing Evolutionary Algorithms on Real-world Numerical Optimization Problems

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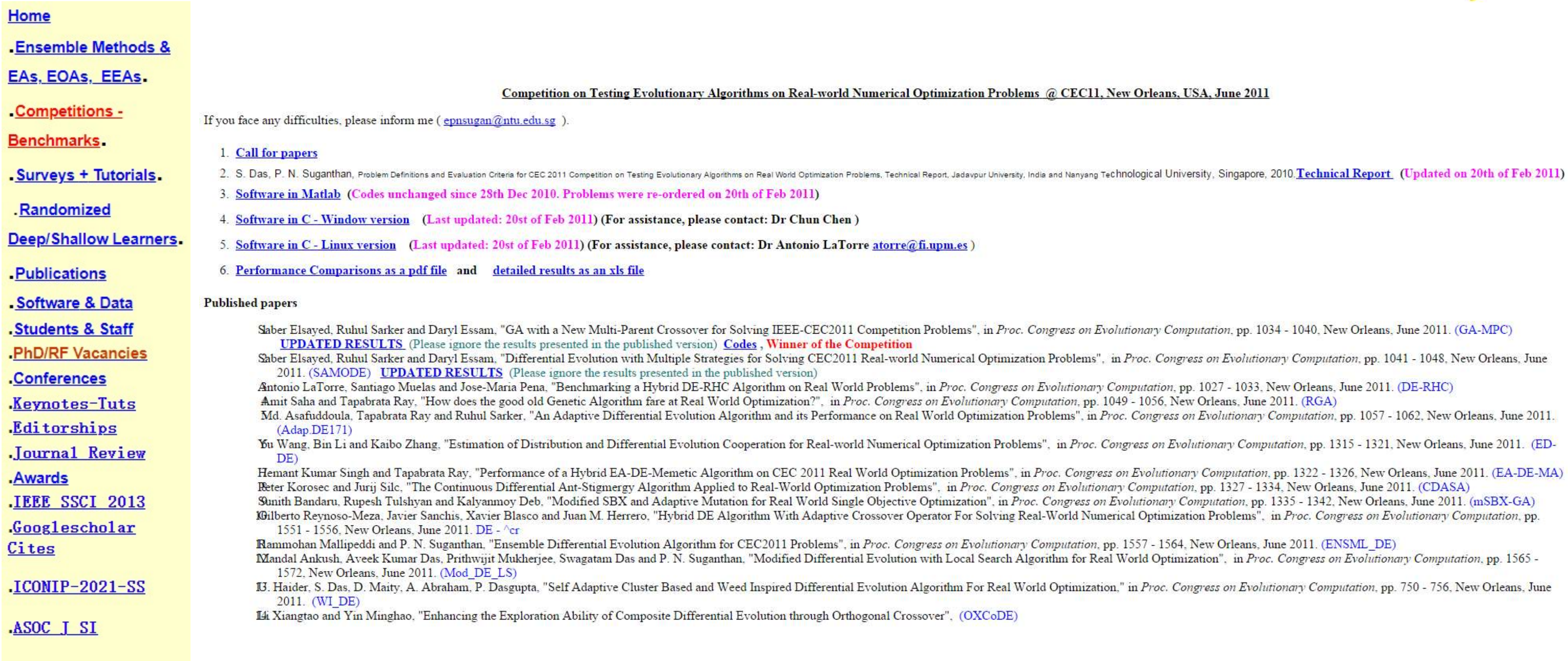

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Competition on Testing Evolutionary Algorithms on Real-world Numerical Optimization Problems @ CEC11, New Orleans, USA, June 2011

If you face any difficulties, please inform me (epnsugan@ntu.edu.sg).

1. Call for papers
2. S. Das, P. N. Suganthan, Problem Definitions and Evaluation Criteria for CEC 2011 Competition on Testing Evolutionary Algorithms on Real World Optimization Problems, Technical Report, Jadavpur University, India and Nanyang Technological University, Singapore, 2010. Technical Report (Updated on 20th of Feb 2011)
3. Software in Matlab (Codes unchanged since 28th Dec 2010. Problems were re-ordered on 20th of Feb 2011)
4. Software in C - Window version (Last updated: 20st of Feb 2011) (For assistance, please contact: Dr Chun Chen)
5. Software in C - Linux version (Last updated: 20st of Feb 2011) (For assistance, please contact: Dr Antonio LaTorre atorre@fi.upm.es)
6. Performance Comparisons as a pdf file and detailed results as an xls file

Published papers

Saber Elsayed, Ruhul Sarker and Daryl Essam, "GA with a New Multi-Parent Crossover for Solving IEEE-CEC2011 Competition Problems", in *Proc. Congress on Evolutionary Computation*, pp. 1034 - 1040, New Orleans, June 2011. (GA-MPC) UPDATED RESULTS (Please ignore the results presented in the published version) Codes , Winner of the Competition

Saber Elsayed, Ruhul Sarker and Daryl Essam, "Differential Evolution with Multiple Strategies for Solving CEC2011 Real-world Numerical Optimization Problems", in *Proc. Congress on Evolutionary Computation*, pp. 1041 - 1048, New Orleans, June 2011. (SAMODE) UPDATED RESULTS (Please ignore the results presented in the published version)

Antonio LaTorre, Santiago Muelas and Jose-Maria Pena, "Benchmarking a Hybrid DE-RHC Algorithm on Real World Problems", in *Proc. Congress on Evolutionary Computation*, pp. 1027 - 1033, New Orleans, June 2011. (DE-RHC)

Amit Saha and Tapabrata Ray, "How does the good old Genetic Algorithm fare at Real World Optimization?", in *Proc. Congress on Evolutionary Computation*, pp. 1049 - 1056, New Orleans, June 2011. (RGA)

Md. Asafuddoula, Tapabrata Ray and Ruhul Sarker, "An Adaptive Differential Evolution Algorithm and its Performance on Real World Optimization Problems", in *Proc. Congress on Evolutionary Computation*, pp. 1057 - 1062, New Orleans, June 2011. (Adap.DE171)

Yu Wang, Bin Li and Kaibo Zhang, "Estimation of Distribution and Differential Evolution Cooperation for Real-world Numerical Optimization Problems", in *Proc. Congress on Evolutionary Computation*, pp. 1315 - 1321, New Orleans, June 2011. (ED-DE)

Hemant Kumar Singh and Tapabrata Ray, "Performance of a Hybrid EA-DE-Memetic Algorithm on CEC 2011 Real World Optimization Problems", in *Proc. Congress on Evolutionary Computation*, pp. 1322 - 1326, New Orleans, June 2011. (EA-DE-MA)

Peter Korosec and Jurij Silc, "The Continuous Differential Ant-Stigmergy Algorithm Applied to Real-World Optimization Problems", in *Proc. Congress on Evolutionary Computation*, pp. 1327 - 1334, New Orleans, June 2011. (CDASA)

Sunith Bandaru, Rupesh Tulshyan and Kalyanmoy Deb, "Modified SBX and Adaptive Mutation for Real World Single Objective Optimization", in *Proc. Congress on Evolutionary Computation*, pp. 1335 - 1342, New Orleans, June 2011. (mSBX-GA)

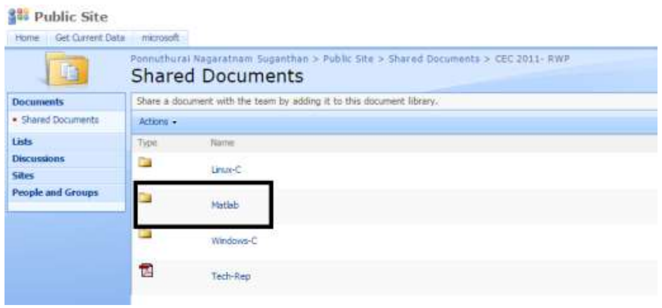
Gilberto Reynoso-Meza, Javier Sanchis, Xavier Blasco and Juan M. Herrero, "Hybrid DE Algorithm With Adaptive Crossover Operator For Solving Real-World Numerical Optimization Problems", in *Proc. Congress on Evolutionary Computation*, pp. 1551 - 1556, New Orleans, June 2011. DE - ^cr

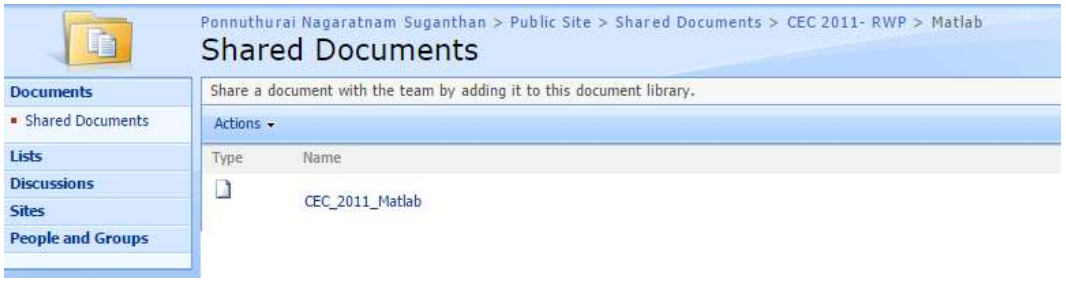
Rammohan Mallipeddi and P. N. Suganthan, "Ensemble Differential Evolution Algorithm for CEC2011 Problems", in *Proc. Congress on Evolutionary Computation*, pp. 1557 - 1564, New Orleans, June 2011. (ENSML_DE)

Mandal Ankush, Aveek Kumar Das, Prithwijit Mukherjee, Swagatam Das and P. N. Suganthan, "Modified Differential Evolution with Local Search Algorithm for Real World Optimization", in *Proc. Congress on Evolutionary Computation*, pp. 1565 - 1572, New Orleans, June 2011. (Mod_DE_LS)

U. Haider, S. Das, D. Maity, A. Abraham, P. Dasgupta, "Self Adaptive Cluster Based and Weed Inspired Differential Evolution Algorithm For Real World Optimization," in *Proc. Congress on Evolutionary Computation*, pp. 750 - 756, New Orleans, June 2011. (WI_DE)

Li Xiangtao and Yin Minghao, "Enhancing the Exploration Ability of Composite Differential Evolution through Orthogonal Crossover". (OXCoDE)





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Sugestion 3: IEEE CEC 2011

Problem Definitions and Evaluation Criteria for CEC 2011 Competition on Testing Evolutionary Algorithms on Real World Optimization Problems

Swagatam Das[1] and P. N. Suganthan[2]

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https://sci2s.ugr.es/sites/default/files/files/TematicWebSites/EAMHCO/contributionsCEC11/RealProblemsTech-Rep.pdf

Ponnuthurai Nagaratnam Suganthan > Public Site > Shared Documents > CEC 2011- RWP

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Problem	Variables	Comments
P01	6	Parameter estimation for frequency-modulated (FM) sound waves.
P02	30	Lennard-Jones Potential Problem.
P03	1	Bifunctional catalyst blend optimal control problem.
P04	1	Optimal control of a non-linear stirred tank reactor.
P05	30	Tersoff potential function minimization problem (instance 1).
P06	30	Tersoff potential function minimization problem (instance 2).
P07	20	Spread spectrum radar polly phase code design.
P08	7	Transmission network expansion planning problem.
P09	122	Large scale transmission pricing problem.
P10	12	Circular antenna array design problem.
P11.1	120	Dynamic economic dispatch problem, instance 1
P11.2	216	Dynamic economic dispatch problem, instance 2
P11.3	6	Static economic load dispatch problem, instance 1
P11.4	13	Static economic load dispatch problem, instance 2
P11.5	15	Static economic load dispatch problem, instance 3
P11.6	40	Static economic load dispatch problem, instance 4
P11.7	140	Static economic load dispatch problem, instance 5
P11.8	96	Hydrothermal scheduling problem, instance 1
P11.9	96	Hydrothermal scheduling problem, instance 2
P11.10	96	Hydrothermal scheduling problem, instance 3
P12	26	Spacecraft trajectory optimization problem.
P13	22	Spacecraft trajectory optimization problem.

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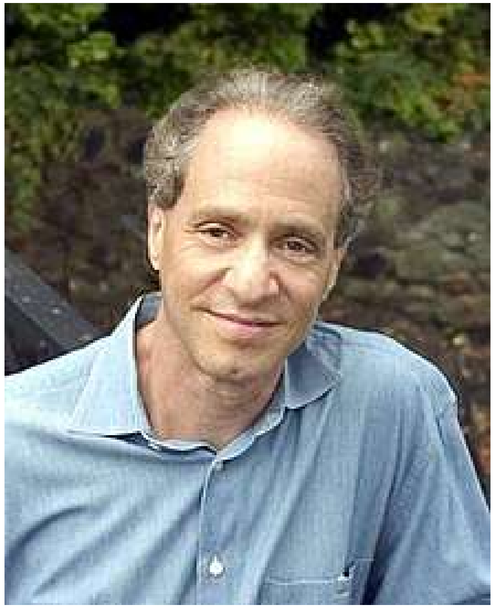
Quote

Artificial intelligence will reach human levels by around 2029. Follow that out further to, say, 2045, we will have multiplied the intelligence, the human biological machine intelligence of our civilization a billion-fold.

Ray Kurzweil (1948-)

He is an American inventor and futurist.



Kurzweil received the 1999 National Medal of Technology and Innovation, the United States' highest honor in technology, from President Clinton in a White House ceremony. He was the recipient of the $500,000 Lemelson-MIT Prize for 2001. And in 2002 he was inducted into the National Inventors Hall of Fame, established by the U.S. Patent Office. He has received 21 honorary doctorates, and honors from three U.S. presidents.

http://www.kurzweilai.net/