The Tunable W-Model Benchmark Problem

Thomas Weise & Zijun Wu · 汤卫思 & 吴自军

tweise@hfuu.edu.cn · http://iao.hfuu.edu.cn

Hefei University, South Campus 2
Faculty of Computer Science and Technology
Institute of Applied Optimization
230601 Shushan District, Hefei, Anhui, China
Econ. & Tech. Devel. Zone, Jinxiu Dadao 99

合肥学院 南艳湖校区/南2区
计算机科学与技术系
应用优化研究所
中国 安徽省 合肥市 蜀山区 230601
经济技术开发区 锦绣大道99号

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Outline

1. Introduction

2. The *W-Model*

3. Experiment

4. Summary

website

Section Outline

These are the slides for paper [1] presented at the BB-DOB workshop at GECCO'2018.

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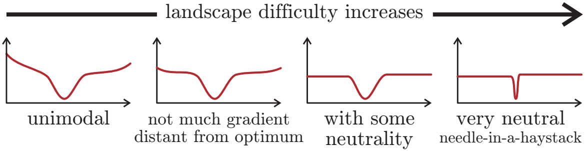

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    - neutrality
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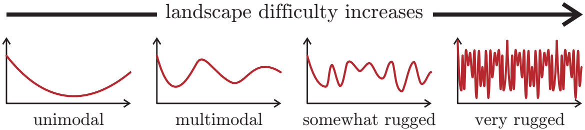

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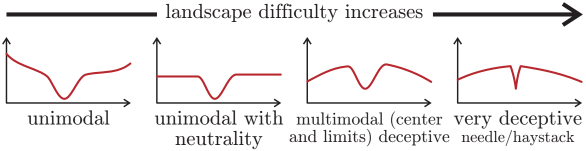
landscape difficulty increases
unimodal
unimodal with neutrality
multimodal (center and limits) deceptive
very deceptive
needle/haystack

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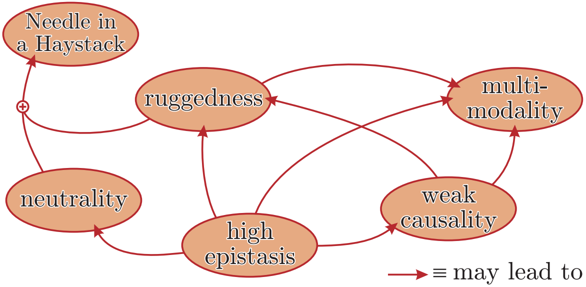
  - ruggedness
  - deceptiveness
  - epistasis



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- So are classical problems like the Traveling Salesman Problem (TSP) [4, 5] or the Maximum Satisfiability Problem (SAT) [6, 7] good candidates?
- Not really. It is not that easy to understand how hard, difficult, rugged, deceptive, or epistatic a TSP or SAT problem is...

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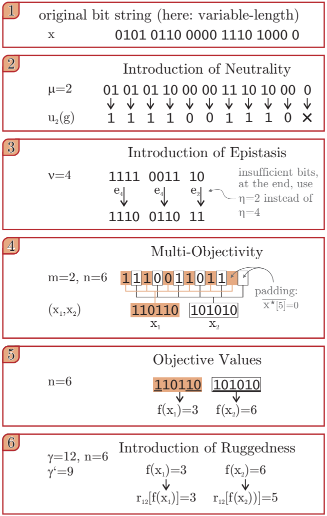
13. have available example data sets with results from example experiments.

The W-Model Tunable Benchmark Problem

- Benchmark Model [1, 8, 9] defined over $\{0,1\}^n$.



1 original bit string (here: variable-length)

x 0101 0110 0000 1110 1000 0

2 Introduction of Neutrality

μ=2 01 01 01 10 00 00 11 10 10 00 0

$u_2(g)$ 1 1 1 1 0 0 1 1 1 0 ×

3 Introduction of Epistasis

ν=4 1111 0011 10

e_4 e_4 e_2

1110 0110 11

insufficient bits, at the end, use η=2 instead of η=4

4 Multi-Objectivity

m=2, n=6 1 1 1 0 0 1 1 0 1 1

padding: $\overline{x^\star[5]}=0$

(x_1,x_2) 110110 101010

x_1 x_2

5 Objective Values

n=6 110110 101010

$f(x_1)=3$ $f(x_2)=6$

6 Introduction of Ruggedness

γ=12, n=6

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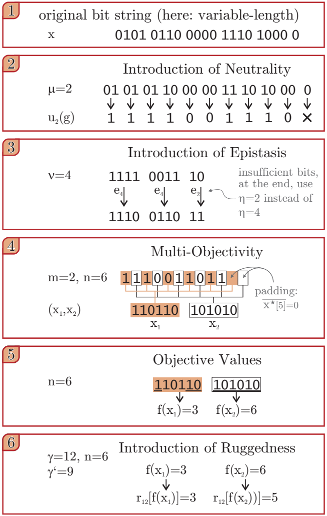

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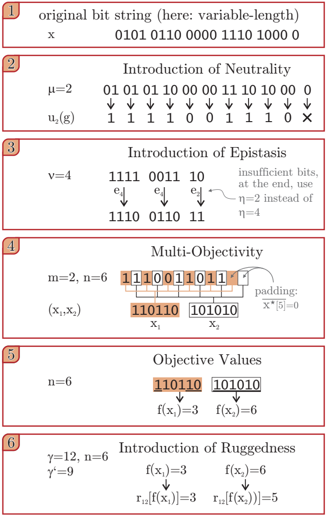
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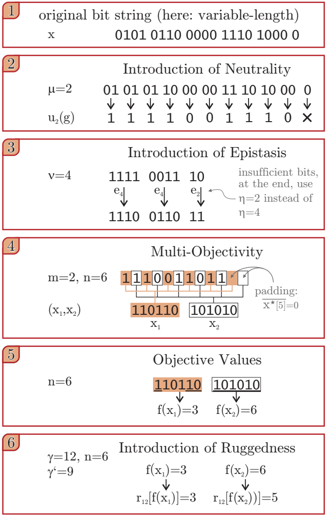

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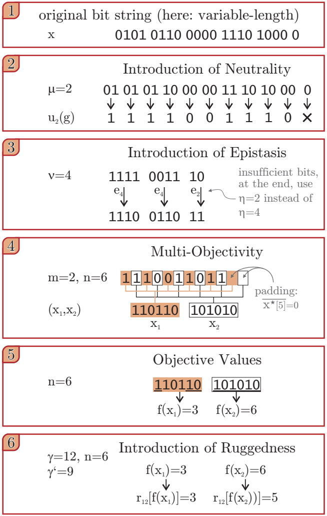

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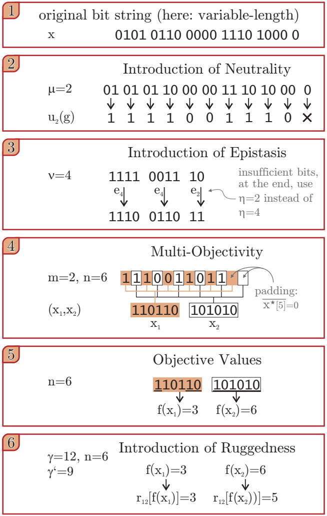

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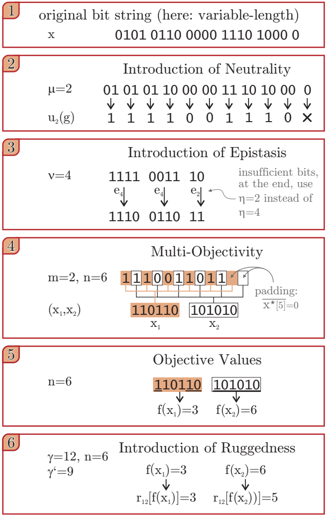

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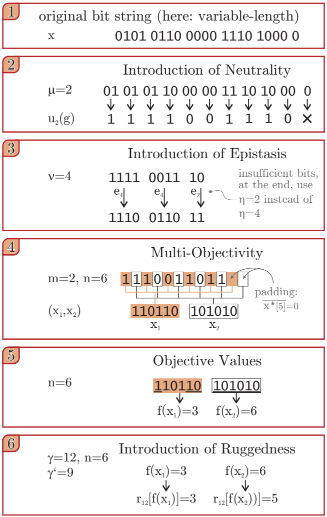

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- Huge example experiment [10] obtained from this implementation with 45 GB of algorithm traces at doi:`10.5281/zenodo.1256883`.

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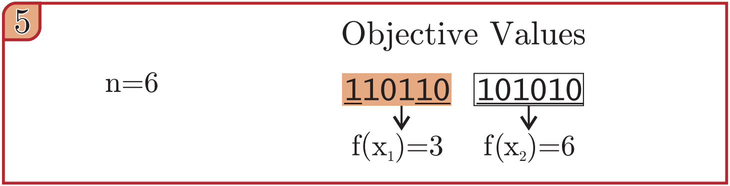

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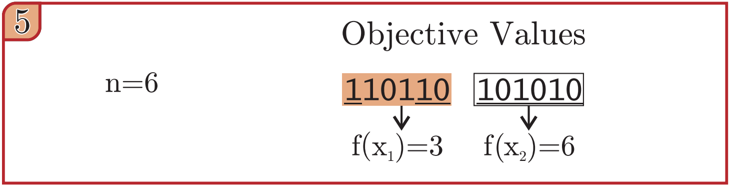

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$\downarrow$ $\downarrow$

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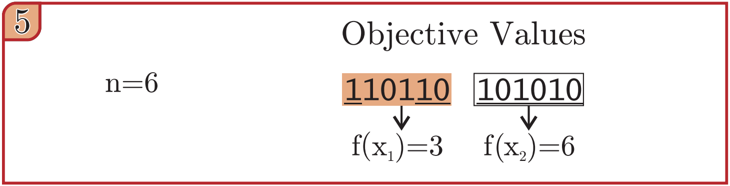

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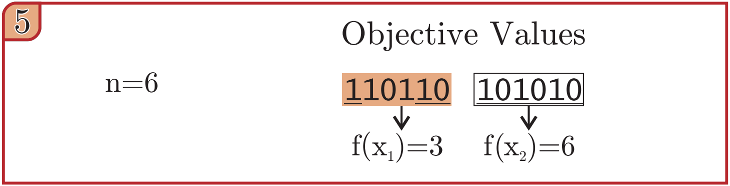
- Fixed-Length Search Space: bit strings of length n.



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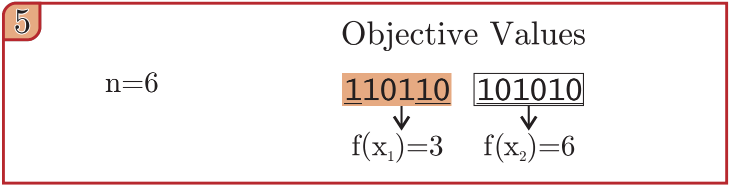
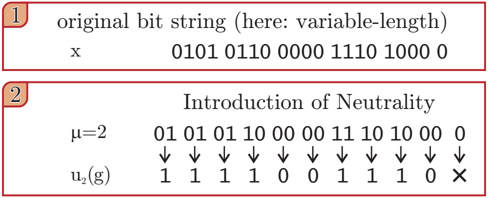
- Goal: minimize the Hamming distance $h(x, x^{\star})$ to $x^{\star} = (0101\ldots)$ of length n.
- Very similar to OneMax problem [11–14].
- Computing of objective function is in $\mathcal{O}(n)$ for bit strings with length $l(x) = n$.
- Fixed-Length Search Space: bit strings of length n.
- Variable-Length Search Space: overly long strings ($l(x) > n$) are cut after position n, strings that are too short are padded with $\overline{x^{\star}}$.



Neutrality Layer

- The application of a search operator is *neutral* if it yields no change in objective value [15, 16].



1 original bit string (here: variable-length)

x 0101 0110 0000 1110 1000 0

2 Introduction of Neutrality

μ=2 01 01 01 10 00 00 11 10 10 00 0

$u_2(g)$ 1 1 1 1 0 0 1 1 1 0 ✕

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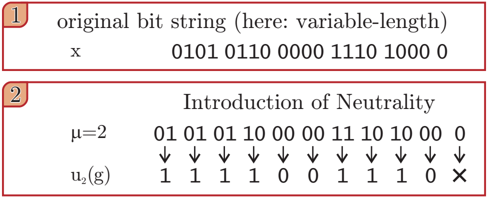

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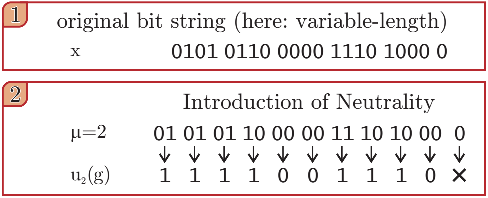

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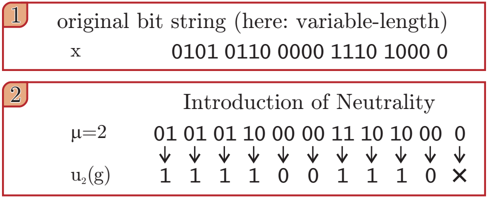

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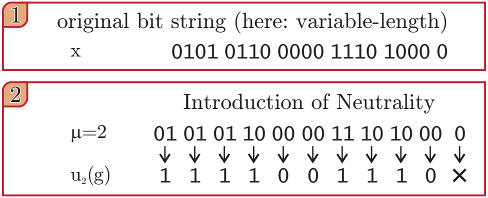
- Fixed-Length Search Space: bit string length now $\mu * n$.
- Variable-Length Search Space: if $l(x)$ no multiple of μ, ignore last $l(x) \bmod \mu$ bits.



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Epistasis Layer

- The interaction between biological genes is epistatic if the effect on the fitness from altering one gene depends on the allelic state of other genes [19, 20].

Epistasis Layer

- Two decision variables (here: bits) interact epistatically, if the contribution of one of these variables to the objective value depends on the value of the other variable [9, 20–22].

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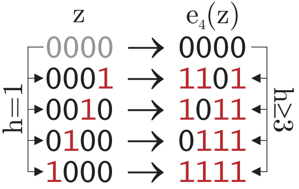
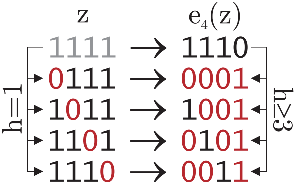


z		$e_4(z)$
0000	$\longrightarrow$	0000
0001	$\longrightarrow$	1101
0010	$\longrightarrow$	1011
0100	$\longrightarrow$	0111
1000	$\longrightarrow$	1111



z		$e_4(z)$
1111	$\longrightarrow$	1110
0111	$\longrightarrow$	0001
1011	$\longrightarrow$	1001
1101	$\longrightarrow$	0101
1110	$\longrightarrow$	0011

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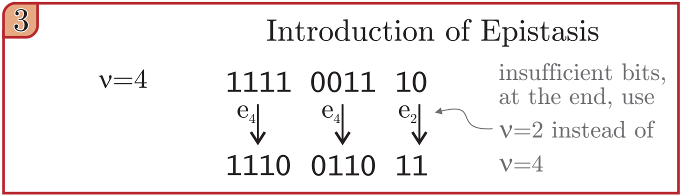
- Each bit in x influences the value of $\nu-1$ bits in $e_\nu(x)$.
- Candidate solutions divided into blocks of length ν to be transformed separately, if block of length $l(x) \bmod \nu$ remains, it is transformed with $e_{l(x) \bmod \nu}$.



3

Introduction of Epistasis

ν=4

1111 0011 10

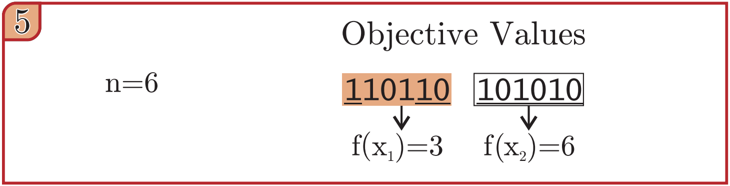
e4 e4 e2

1110 0110 11

insufficient bits, at the end, use ν=2 instead of ν=4

Multi-Objectivity Layer

- Many optimization problems are multi-objective, i.e., involve multiple, possible conflicting criteria [23–25]



5

Objective Values

n=6

$\underline{1}101\underline{10}$ $\boxed{\underline{101010}}$

$f(x_1)=3$ $f(x_2)=6$

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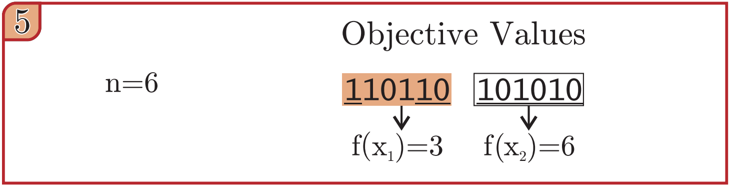
- We simply interleave m instances of the *W-Model* to get an m-objective problem.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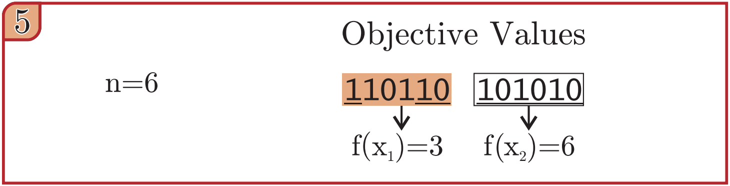
- We simply interleave m instances of the *W-Model* to get an m-objective problem.
- Disagreement in the orthogonal objective functions can be simulated via epistasis $\nu > 2$.



Ruggedness and Deceptiveness Layer

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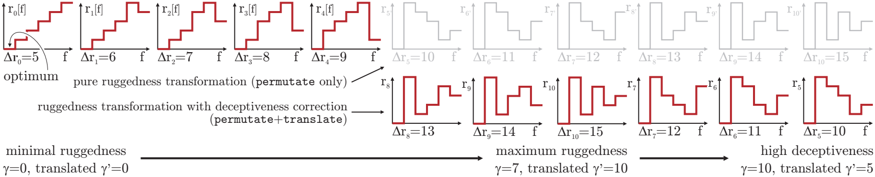
  2. They must preserve the optimal value, i.e., $r_{\gamma'}[0] = 0$.
  3. $\Delta(r_{\gamma'}) = n + \gamma'$.
- With $\gamma' \in 0 \ldots (\hat{\Delta} - n)$, we can fine-tune the ruggedness.

Ruggedness and Deceptiveness Layer

- Such permutations can be generated using the algorithm defined in [1]



Ruggedness and Deceptiveness Layer

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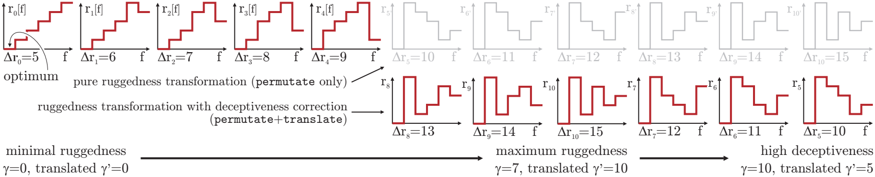
- Original algorithm produces alternating sequences of rugged and deceptive problems, the latter are much harder.



pure ruggedness transformation (`permutate` only)

ruggedness transformation with deceptiveness correction (`permutate`+`translate`)

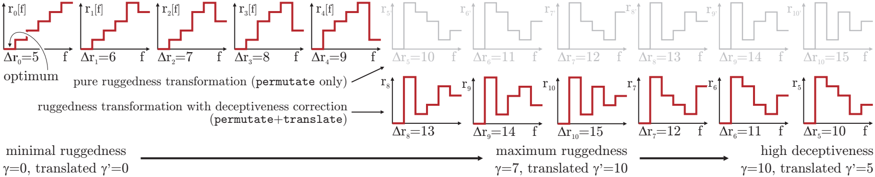
minimal ruggedness γ=0, translated γ'=0

maximum ruggedness γ=7, translated γ'=10

high deceptiveness γ=10, translated γ'=5

Ruggedness and Deceptiveness Layer

- Such permutations can be generated using the algorithm defined in [1]
- Original algorithm produces alternating sequences of rugged and deceptive problems, the latter are much harder.
- Re-arrangement into permutations $r_{\gamma'}$ which nicely blend from smooth to rugged to deceptive problems.



r0[f]
r1[f]
r2[f]
r3[f]
r4[f]
r5'
r6'
r7'
r8'
r9'
r10'
Δr0=5 f
Δr1=6 f
Δr2=7 f
Δr3=8 f
Δr4=9 f
Δr5=10 f
Δr6=11 f
Δr7=12 f
Δr8=13 f
Δr9=14 f
Δr10=15 f
optimum
pure ruggedness transformation (permutate only)
ruggedness transformation with deceptiveness correction (permutate+translate)
r8
r9
r10
r7
r6
r5
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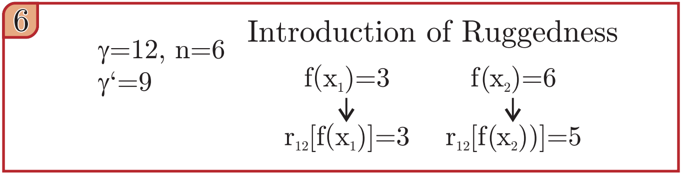
- Such permutations can be generated using the algorithm defined in [1]
- Original algorithm produces alternating sequences of rugged and deceptive problems, the latter are much harder.
- Re-arrangement into permutations $r_{\gamma'}$ which nicely blend from smooth to rugged to deceptive problems.
- Permutation serves as lookup-table to map objective values.



6

γ=12, n=6

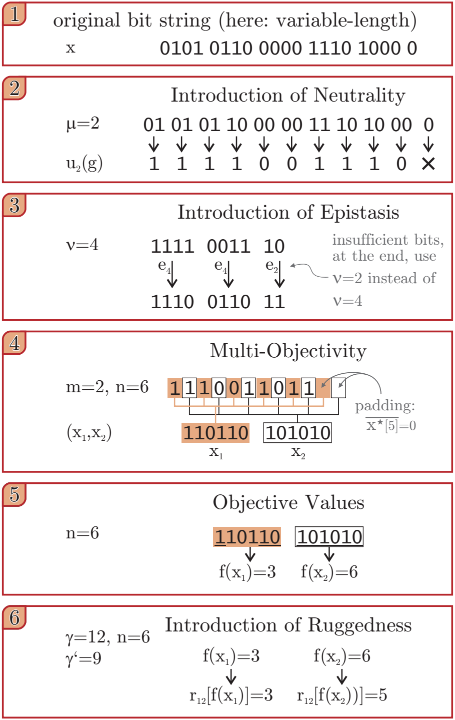
γ‘=9

Introduction of Ruggedness

$$\mathrm{f}(\mathrm{x}_1)=3 \downarrow \mathrm{r}_{12}[\mathrm{f}(\mathrm{x}_1)]=3$$

$$\mathrm{f}(\mathrm{x}_2)=6 \downarrow \mathrm{r}_{12}[\mathrm{f}(\mathrm{x}_2))]=5$$

Summary



1 original bit string (here: variable-length)

x 0101 0110 0000 1110 1000 0

2 Introduction of Neutrality

$\mu=2$ 01 01 01 10 00 00 11 10 10 00 0

$u_2(g)$ 1 1 1 1 0 0 1 1 1 0 ×

3 Introduction of Epistasis

$\nu=4$ 1111 0011 10

e_4 e_4 e_2

1110 0110 11

insufficient bits, at the end, use $\nu=2$ instead of $\nu=4$

4 Multi-Objectivity

$m=2$, $n=6$ 1 1 1 0 0 1 1 0 1 1

padding: $\overline{x^{\star}}[5]=0$

(x_1,x_2) 110110 101010

x_1 x_2

5 Objective Values

$n=6$ 110110 101010

$f(x_1)=3$ $f(x_2)=6$

6 Introduction of Ruggedness

$\gamma=12$, $n=6$

$\gamma'=9$

$f(x_1)=3$ $f(x_2)=6$

$r_{12}[f(x_1)]=3$ $r_{12}[f(x_2))]=5$

Section Outline

These are the slides for paper [1] presented at the BB-DOB workshop at GECCO'2018.

1. Introduction
2. The *W-Model*
3. Experiment
4. Summary

website

Experiments

- Extensive experiments for the variable-length representation with multi-objectivity were performed in [28] and we use this data here.

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- Extensive experiments for the variable-length representation with multi-objectivity were performed in [28] and we use this data here.
- Now, a much bigger dataset for the fixed-length representation and a single-objective $(m = 1)$ is available in [29].

Experiments

- Extensive experiments for the variable-length representation with multi-objectivity were performed in [28] and we use this data here.
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  - population size 1000,
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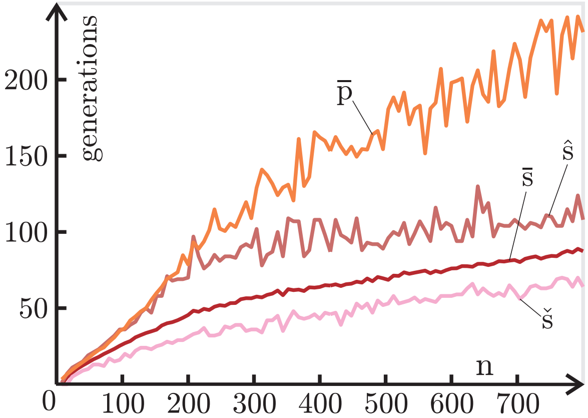
    - variable-length bit string genome with a maximum string length of 8000 bits.
- We distinguish *success* (after s generations), i.e., finding a string x with $f(x) = 0$ (but which may be too long) and *perfection*, i.e., finding $x^{\star}$ (after $p \geq s$ generations).

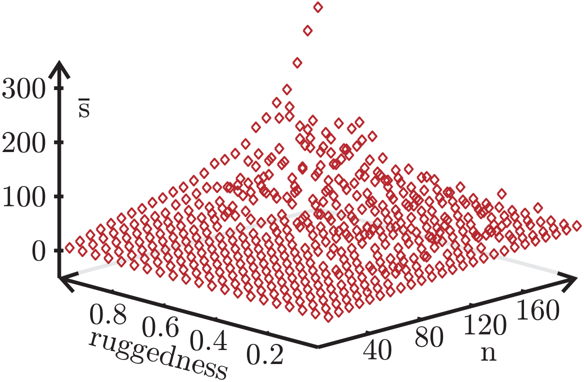
Basic Problem n

- The minimum, average, and maximum success generations $\check{s}$, $\overline{s}$, and $\hat{s}$ measured rise almost linearly after the basic problem parameter n has exceeded 300 bits.



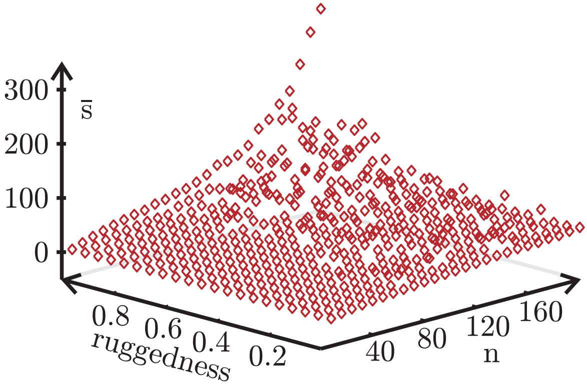
Ruggedness + Basic Problem n

- Ruggedness parameter normalized into the range $[0, 1]$, because its range depends on n.



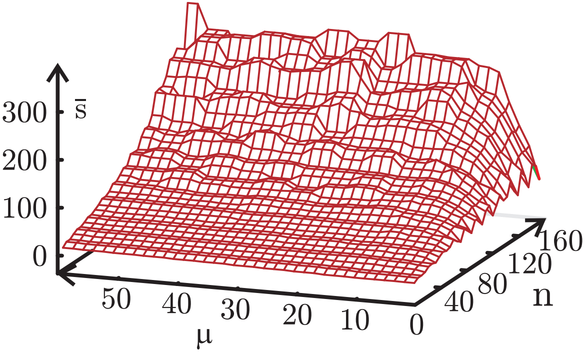
Ruggedness + Basic Problem n

- Ruggedness parameter normalized into the range $[0, 1]$, because its range depends on n.
- Apart from a few peaks in the diagram occurring for $n > 70$, the problem hardness, as expected, increases very fast with the ruggedness.



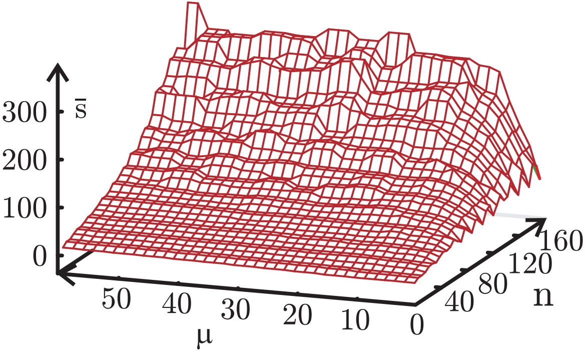
Neutrality μ + Basic Problem n

- Until a degree of $\mu \approx 10$, the problems rapidly gets harder with rising redundancy μ.



Neutrality μ + Basic Problem n

- Until a degree of $\mu \approx 10$, the problems rapidly gets harder with rising redundancy μ.
- From there on, a further increase of μ only leads to a very slow increase in hardness.



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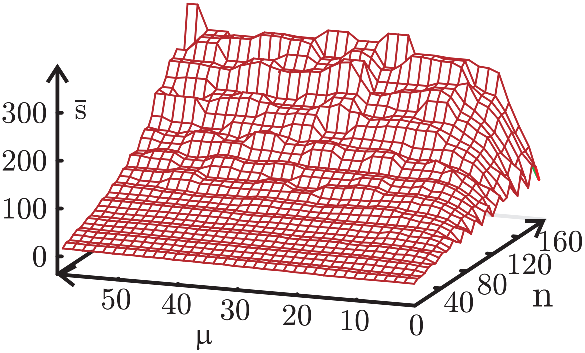

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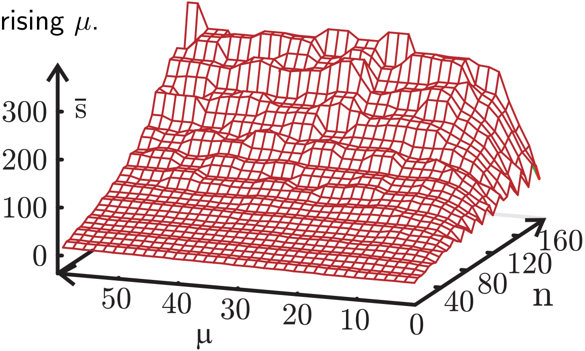
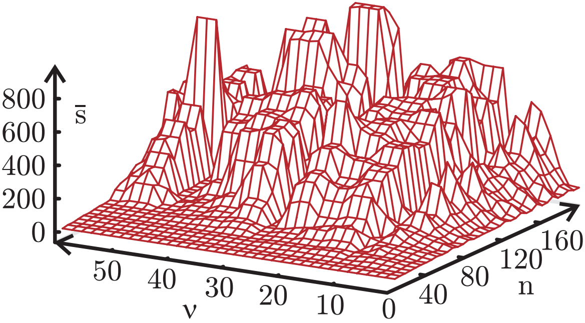
- Until a degree of $\mu \approx 10$, the problems rapidly gets harder with rising redundancy μ.
- From there on, a further increase of μ only leads to a very slow increase in hardness.
- Probably cause: for crossover, larger μ make no big difference.
- Experiments with lower crossover rate led to quick decrease of performance for rising μ.



Epistasis ν + Basic Problem n

- Problem complexity steeply increases with rising epistasis (values of ν).



Epistasis ν + Basic Problem n

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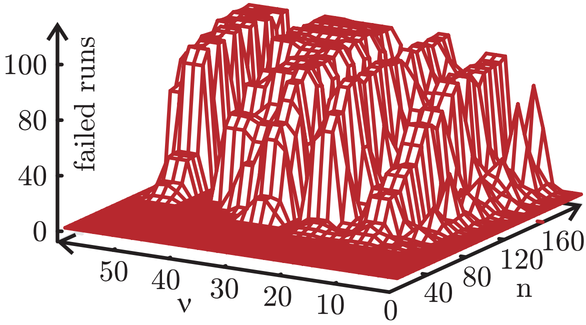
- Number of runs that cannot solve problem in 1000 generations quickly rises with ν.



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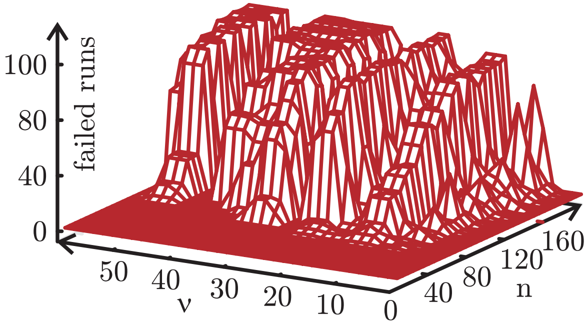
- Problems for which $\nu = 2 + 4v : v \in \mathbb{N}$ are unexpectedly easy.



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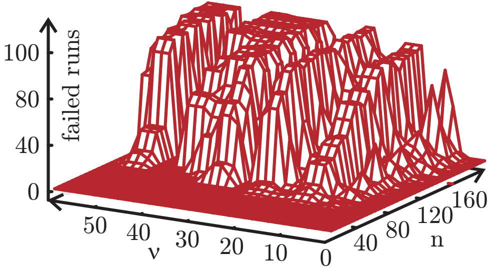

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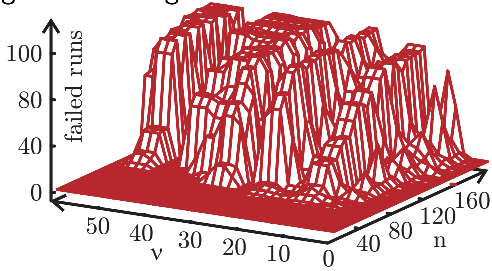
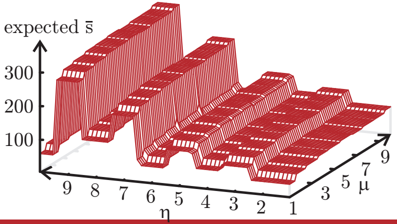
- We suggest not using these settings.



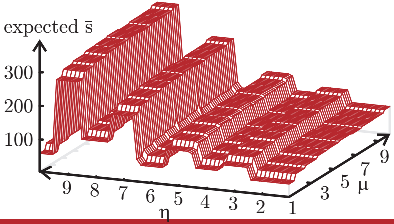
Expected Epistasis ν + Neutrality μ

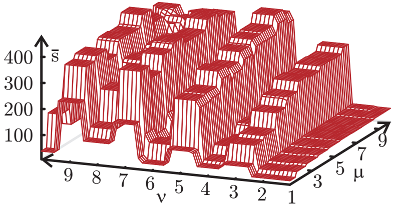
- Two separate experiments with either neutrality or epistasis added together: “expected $\overline{s}$”



Expected Epistasis ν + Neutrality μ

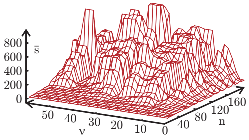
- Two separate experiments with either neutrality or epistasis added together: "expected $\overline{s}$"
- Actual experiment with both neutrality and epistasis: shape similar to expectation, but 100 generations harder

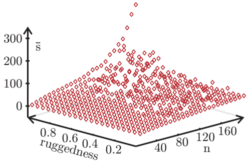


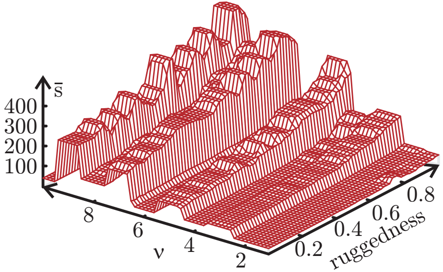


Real Epistasis ν + Ruggedness

- If both epistasis and ruggedness are used, results look similar to expectations of adding the results with only ruggedness to those with only epistasis.

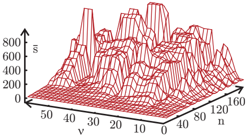


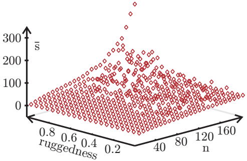


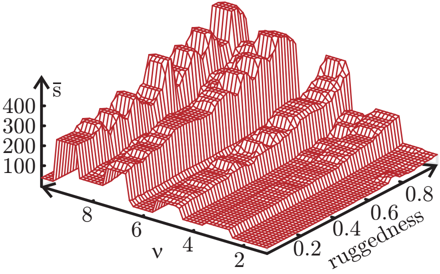


Real Epistasis ν + Ruggedness

- If both epistasis and ruggedness are used, results look similar to expectations of adding the results with only ruggedness to those with only epistasis.
- A rising ruggedness component leads, however, to over-proportional increases in $\overline{s}$.







Section Outline

These are the slides for paper [1] presented at the BB-DOB workshop at GECCO'2018.

1 Introduction

2 The *W-Model*

3 Experiment

4 Summary

website

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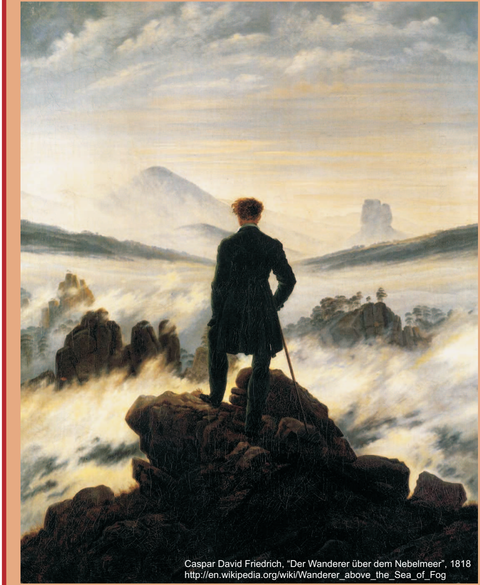
- It can be applied with a fixed-length and a variable-length represention.
- Our old experiments with the variable-length representation show that it behaves well and as expected.
- A new implementation [10] is provided along with new results for the fixed-length representation in [29].

谢谢

Thank you

Thomas Weise & Zijun Wu [汤卫思 & 吴自军]
tweise@hfuu.edu.cn
http://iao.hfuu.edu.cn

Hefei University, South Campus 2
Institute of Applied Optimization
Shushan District, Hefei, Anhui, China



Caspar David Friedrich, “Der Wanderer über dem Nebelmeer”, 1818
http://en.wikipedia.org/wiki/Wanderer_above_the_Sea_of_Fog

Bibliography

Bibliography I

1. Thomas Weise and Zijun Wu. Difficult features of combinatorial optimization problems and the tunable *W-Model* benchmark problem for simulating them. In *Black Box Discrete Optimization Benchmarking (BB-DOB) Workshop in Companion Material Proceedings of the Genetic and Evolutionary Computation Conference (GECCO 2018), July 15–19, 2018, Kyoto, Japan*, pages 1769–1776. ACM. doi: 10.1145/3205651.3208240. ISBN: 978-1-4503-5764-7. Additional experimental results with the *W-Model*, which were not used in this paper, can be found in [29] at doi:10.5281/zenodo.1256883 based on implementation [10].
2. Thomas Weise, Raymond Chiong, and Ke Tang. Evolutionary optimization: Pitfalls and booby traps. *Journal of Computer Science and Technology (JCST)*, 27:907–936, 2012. doi: 10.1007/s11390-012-1274-4.
3. Thomas Weise, Michael Zapf, Raymond Chiong, and Antonio Jesús Nebro Urbaneja. Why is optimization difficult? In Raymond Chiong, editor, *Nature-Inspired Algorithms for Optimisation*, volume 193 of *Studies in Computational Intelligence*, chapter 1, pages 1–50. Springer-Verlag, Berlin/Heidelberg, 2009. ISBN 978-3-642-00266-3. doi: 10.1007/978-3-642-00267-0_1.
4. David Lee Applegate, Robert E. Bixby, Vašek Chvátal, and William John Cook. *The Traveling Salesman Problem: A Computational Study*. Princeton University Press, Princeton, NJ, USA, 2007.
5. Thomas Weise, Raymond Chiong, Ke Tang, Jörg Lässig, Shigeyoshi Tsutsui, Wenxiang Chen, Zbigniew Michalewicz, and Xin Yao. Benchmarking optimization algorithms: An open source framework for the traveling salesman problem. *IEEE Computational Intelligence Magazine (CIM)*, 9(3):40–52, August 2014. doi: 10.1109/MCI.2014.2326101.
6. *Proc. of the 18th Intl. Conf. on Theory and Applications of Satisfiability Testing (SAT 2015)*, volume 9340 of *Lecture Notes in Computer Science book series (LNCS)*, Cham, September 24-27, 2015. Springer. ISBN 978-3-319-24317-7. doi: 10.1007/978-3-319-24318-4.
7. Holger H. Hoos and Thomas Stützle. SATLIB: An online resource for research on SAT. In *SAT2000 – Highlights of Satisfiability Research in the Year 2000*, volume 63 of *Frontiers in Artificial Intelligence and Applications*, pages 283–292, Amsterdam, The Netherlands, 2000. IOS Press. ISBN 978-1-58603-061-2. URL `http://www.cs.ubc.ca/~hoos/Publ/sat2000-satlib.pdf`.
8. Thomas Weise, Stefan Niemczyk, Hendrik Skubch, Roland Reichle, and Kurt Geihs. A tunable model for multi-objective, epistatic, rugged, and neutral fitness landscapes. In *Genetic and Evolutionary Computation Conference*, pages 795–802, Atlanta, GA, USA, 2008. ACM Press.
9. Thomas Weise. *Global Optimization Algorithms – Theory and Application*. it-weise.de (self-published), Germany, 2009. URL `http://www.it-weise.de/projects/book.pdf`.

Bibliography II

10. Thomas Weise. The *W-Model*, a tunable black-box discrete optimization benchmarking (bb-dob) problem, implemented for the bb-dob@gecco workshop, June 2018. URL `http://github.com/thomasWeise/BBDOB_W_Model`. Open source implementation *W-Model* [1] provided in a GitHub repository, used in [29].
11. David H. Ackley. *A Connectionist Machine for Genetic Hillclimbing*. PhD thesis, Carnegy Mellon University (CMU), Pittsburgh, PA, USA, 1987.
12. Dirk Thierens and David Edward Goldberg. Convergence models of genetic algorithm selection schemes. In *Proc. of the Third Conf. on Parallel Problem Solving from Nature (PPSN III)*, volume 866/1994 of *Lecture Notes in Computer Science (LNCS)*, pages 119–129, Berlin, Germany, October 9–14, 1994. Springer-Verlag GmbH. ISBN 0387584846. doi: 10.1007/3-540-58484-6_256.
13. Brad L. Miller and David Edward Goldberg. Genetic algorithms, selection schemes, and the varying effects of noise. *Evolutionary Computation*, 4(2):113–131, 1996. doi: 10.1162/evco.1996.4.2.113.
14. Tobias Blickle and Lothar Thiele. A comparison of selection schemes used in genetic algorithms. TIK-Report 11, ETH Zürich, Department of Electrical Engineering, Computer Engineering and Networks Laboratory (TIK), Zürich, Switzerland, December 1995. URL `ftp://ftp.tik.ee.ethz.ch/pub/publications/TIK-Report11.ps`.
15. Christian M. Reidys and Peter F. Stadler. Neutrality in fitness landscapes. *Journal of Applied Mathematics and Computation*, 117(2–3):321–350, 2001. doi: 10.1016/S0096-3003(99)00166-6.
16. Lionel Barnett. Ruggedness and neutrality – the nkp family of fitness landscapes. In *Proc. of the Sixth Intl. Conf. on Artificial Life (Artificial Life VI)*, volume 6 of *Complex Adaptive Systems*, pages 18–27, Cambridge, MA, USA, June 27–29, 1998. MIT Press. ISBN 0-262-51099-5.
17. Joshua D. Knowles and Richard A. Watson. On the utility of redundant encodings in mutation-based evolutionary search. In *Proc. of the 7th Intl. Conf. on Parallel Problem Solving from Nature (PPSN VII)*, volume 2439 of *Lecture Notes in Computer Science (LNCS)*, pages 88–98, Berlin, Germany, September 7–11, 2002. Springer-Verlag GmbH. ISBN 3-540-44139-5. doi: 10.1007/3-540-45712-7_9.
18. Franz Rothlauf. *Representations for Genetic and Evolutionary Algorithms*, volume 104 of *Studies in Fuzziness and Soft Computing*. Springer-Verlag, Berlin/Heidelberg, second edition, 2006. doi: 10.1007/3-540-32444-5.
19. Jay L. Lush. Progeny test and individual performance as indicators of an animal's breeding value. *Journal of Dairy Science (JDS)*, 18(1):1–19, 1935.
20. Lee Altenberg. Nk fitness landscapes. In Thomas Bäck, David B. Fogel, and Zbigniew Michalewicz, editors, *Handbook of Evolutionary Computation*, chapter B2.7.2. Oxford University Press, Oxford, England, UK, 1997.

Bibliography III

21. Yuval Davidor. Epistasis variance: A viewpoint on GA-hardness. In *Proc. of the First Workshop on Foundations of Genetic Algorithms (FOGA'90)*, pages 23–35, San Francisco, CA, USA, July 15–18, 1990. Morgan Kaufmann Publishers Inc. ISBN 1-55860-170-8.
22. Bart Naudts and Alain Verschoren. Epistasis on finite and infinite spaces. In *Proc. of the 8th Intl. Conf. on Systems Research, Informatics and Cybernetics (InterSymp'96)*, pages 19–23, Tecumseh, ON, Canada, August 14–18, 1996. Intl. Institute for Advanced Studies in Systems Research and Cybernetic (IIAS).
23. Kalyanmoy Deb. *Multi-Objective Optimization Using Evolutionary Algorithms*. Wiley Interscience Series in Systems and Optimization. John Wiley & Sons Ltd., New York, NY, USA, 2001. ISBN 047187339X.
24. Carlos Artemio Ceollo Coello. An updated survey of evolutionary multiobjective optimization techniques: State of the art and future trends. In *Congress on Evolutionary Computation (CEC)*, pages 3–13, Piscataway, NJ, USA, July 6–9, 1999. IEEE Press. doi: 10.1109/CEC.1999.781901.
25. Carlos M. Fonseca and Peter J. Fleming. Multiobjective optimization and multiple constraint handling with evolutionary algorithms – part i: A unified formulation. *IEEE Transactions on Systems, Man, and Cybernetics, Part A: Systems and Humans*, 28(1):26–37, 1998.
26. Charles Campbell Palmer and Aaron Kershenbaum. Representing trees in genetic algorithms. In *Proc. of the 1st IEEE Conf. on Evolutionary Comput. (CEC'94)*, volume 1, pages 379–384, Piscataway, NJ, USA, June 27–29, 1994. IEEE Comp. Soc. ISBN 0-7803-1899-4.
27. Charles Campbell Palmer. *An approach to a problem in network design using genetic algorithms*. PhD thesis, Polytechnic University, New York, NY, 1994.
28. Stefan Niemczyk. Ein benchmark problem für globale optimierungsverfahren. Bachelor's thesis, Distributed Systems Group, University of Kassel, May 2008. Supervisor: Thomas Weise.
29. Thomas Weise. Results for several simple algorithms on the *W-Model* for black-box discrete optimization benchmarking, June 2018. URL `https://doi.org/10.5281/zenodo.1256883`. Based on the implementation of *W-Model* [1] given in [10].