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Metaheuristics for Smart Manufacturing

8. Outlook

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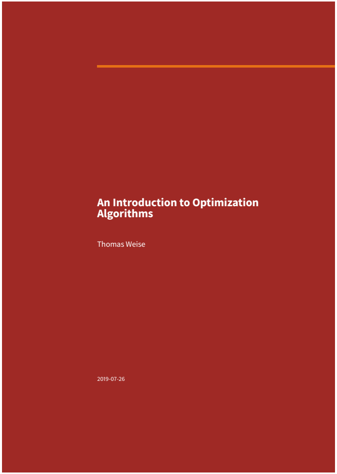
1. What else can we do?
2. Limits
3. Summary

The slides are available at http://iao.hfuu.edu.cn/155, the book at http://thomasweise.github.io/aitoa, and the source code at http://www.github.com/thomasWeise/aitoa-code

course book

course material

The contents of this course are available as free electronic book *"An Introduction to Optimization Algorithms"* [1] at http://thomasweise.github.io/aitoa in pdf, html, azw3, and epub format, created with our bookbuildeR tool chain.



Section Outline

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- But there is so much more, much more can be done!

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- But these are other stories. . .

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- any algorithm (for non-trivial problems) takes longer for larger inputs…
- This is one of the biggest obstacles for practical applications of metaheuristic optimization, in my opinion.

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- But in an enterprise, even 1% of improvement can mean millions of RMB...

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- I hope this course was useful and interesting to you.
- You can find a much more comprehensive discussion in our book [1].

谢谢
Thank you

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

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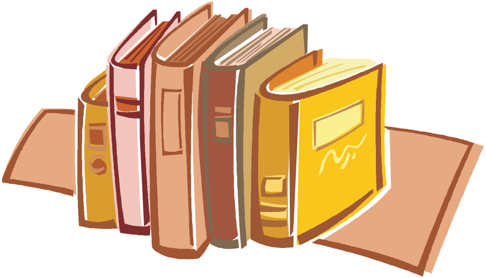

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