合肥學院
HEFEI UNIVERSITY

Metaheuristics for Smart Manufacturing

1. Introduction

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Outline

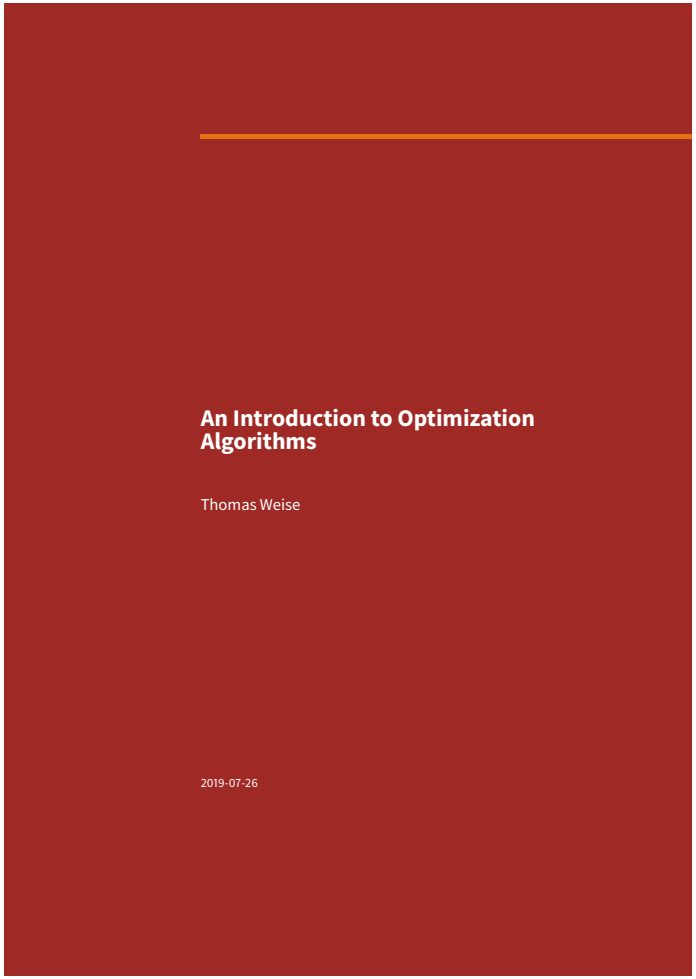
The slides are available at http://iao.hfuu.edu.cn/155, the book at http://thomasweise.github.io/aitoa, and the source code at http://www.github.com/thomasWeise/aitoa-code

course book

course material

An Introduction to Optimization Algorithms

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.

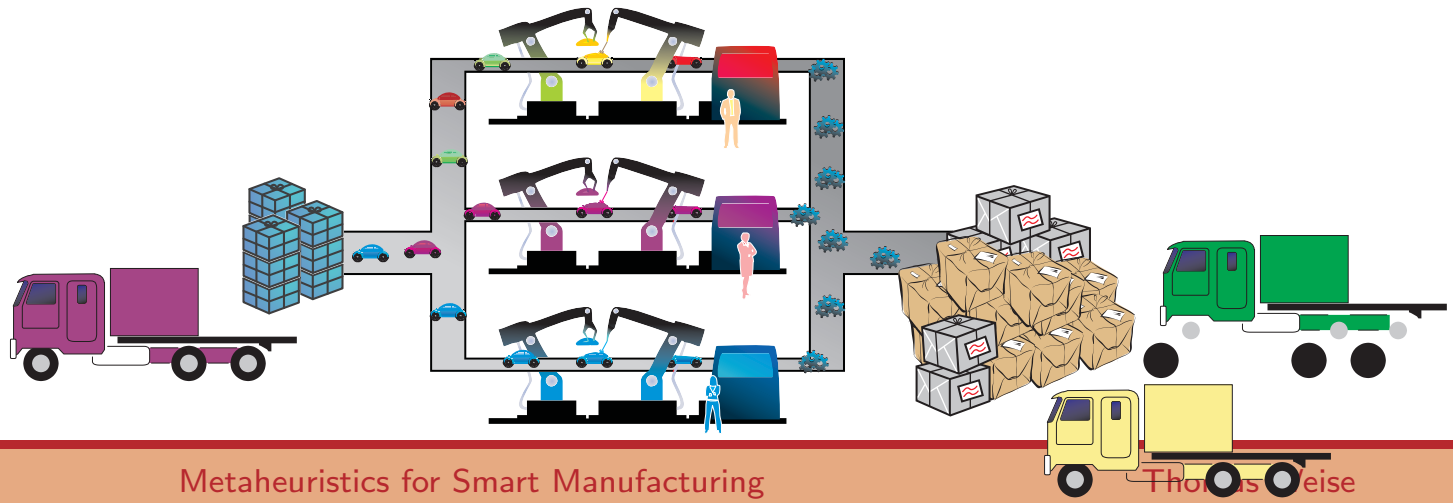


Section Outline

What is Smart Manufacturing?

Smart Manufacturing [2] . . .

- has the goal of optimizing development, production, and logistics.



Intelligent Decisions
by Intelligent Software

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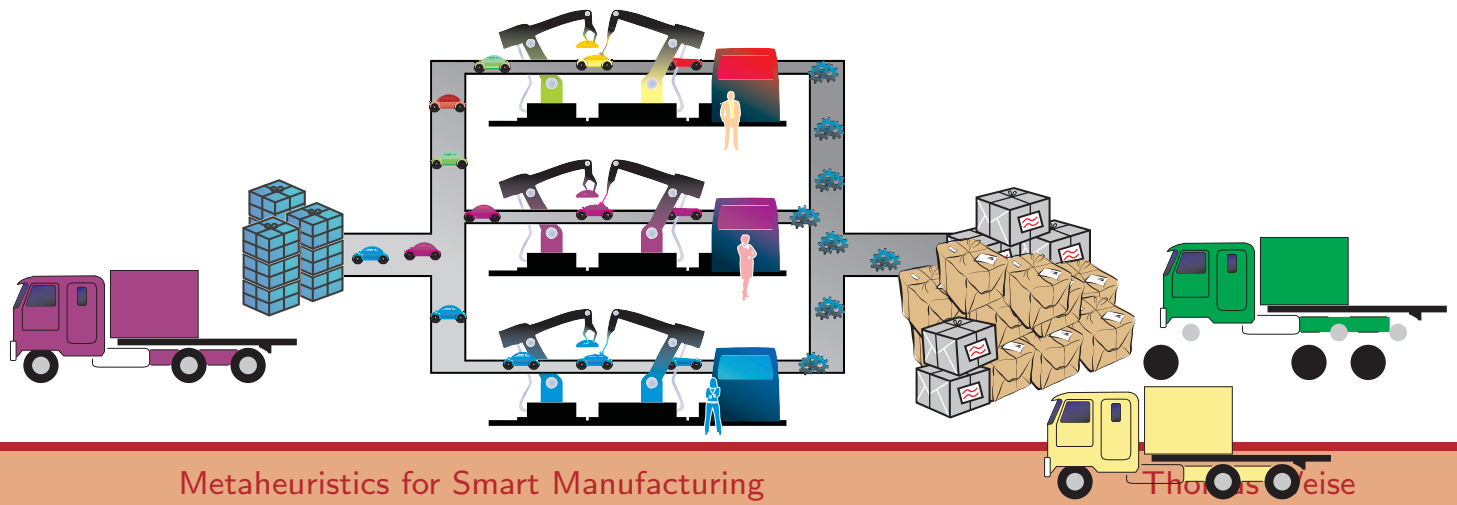

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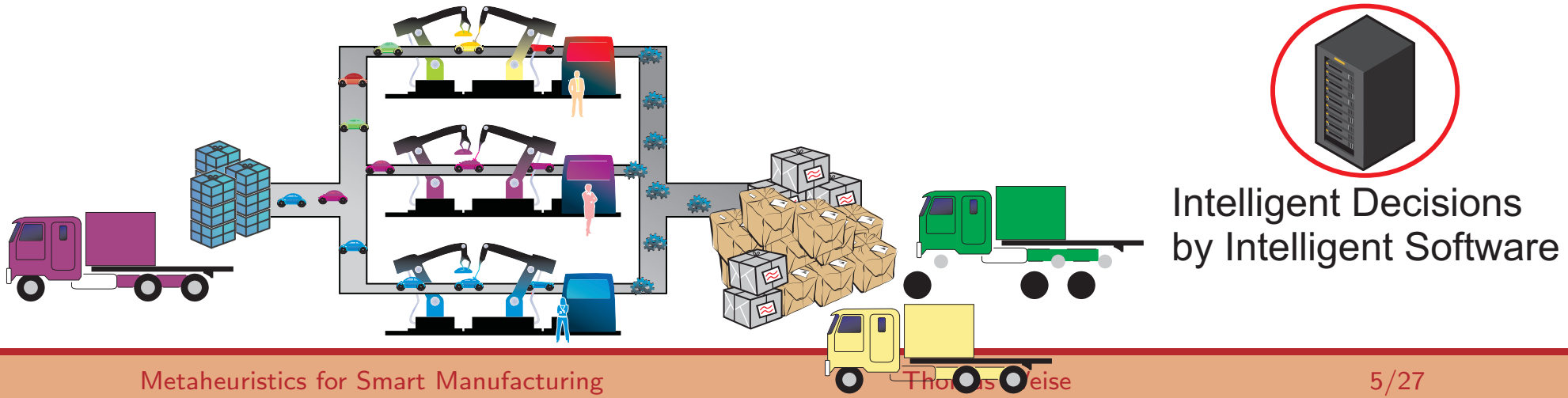
- utilizes advanced information and manufacturing technologies to enable flexibility in production processes to address a dynamic market.



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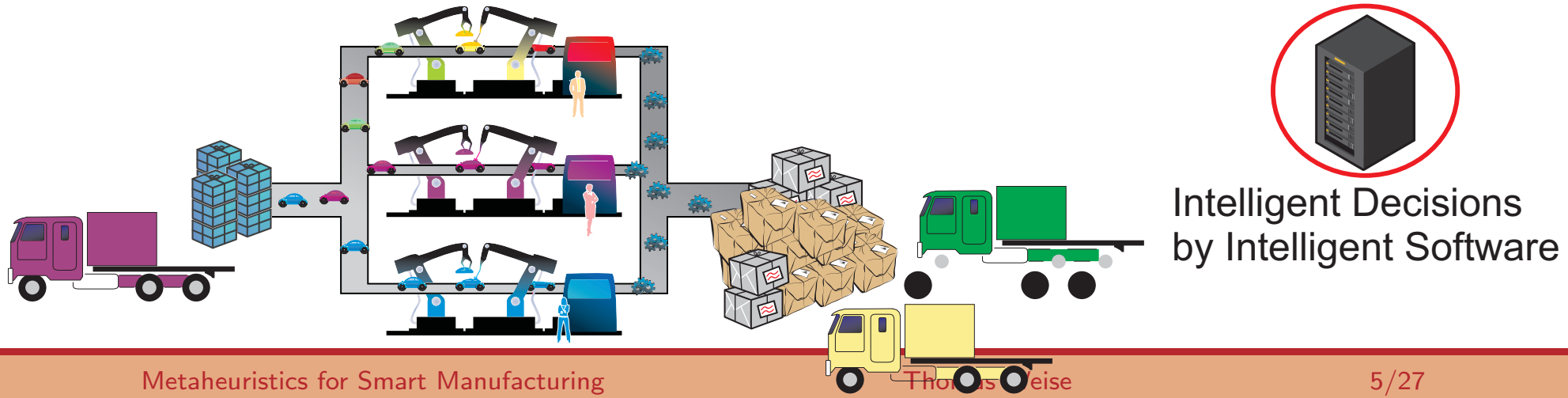
- employs computer control and high levels of adaptability in the multi-phase process of creating a product from raw material.
- utilizes advanced information and manufacturing technologies to enable flexibility in production processes to address a dynamic market.
- requires increased workforce training for flexibility and use of the technology instead of simple repetitive tasks as in traditional manufacturing.



Industry 4.0 [4]

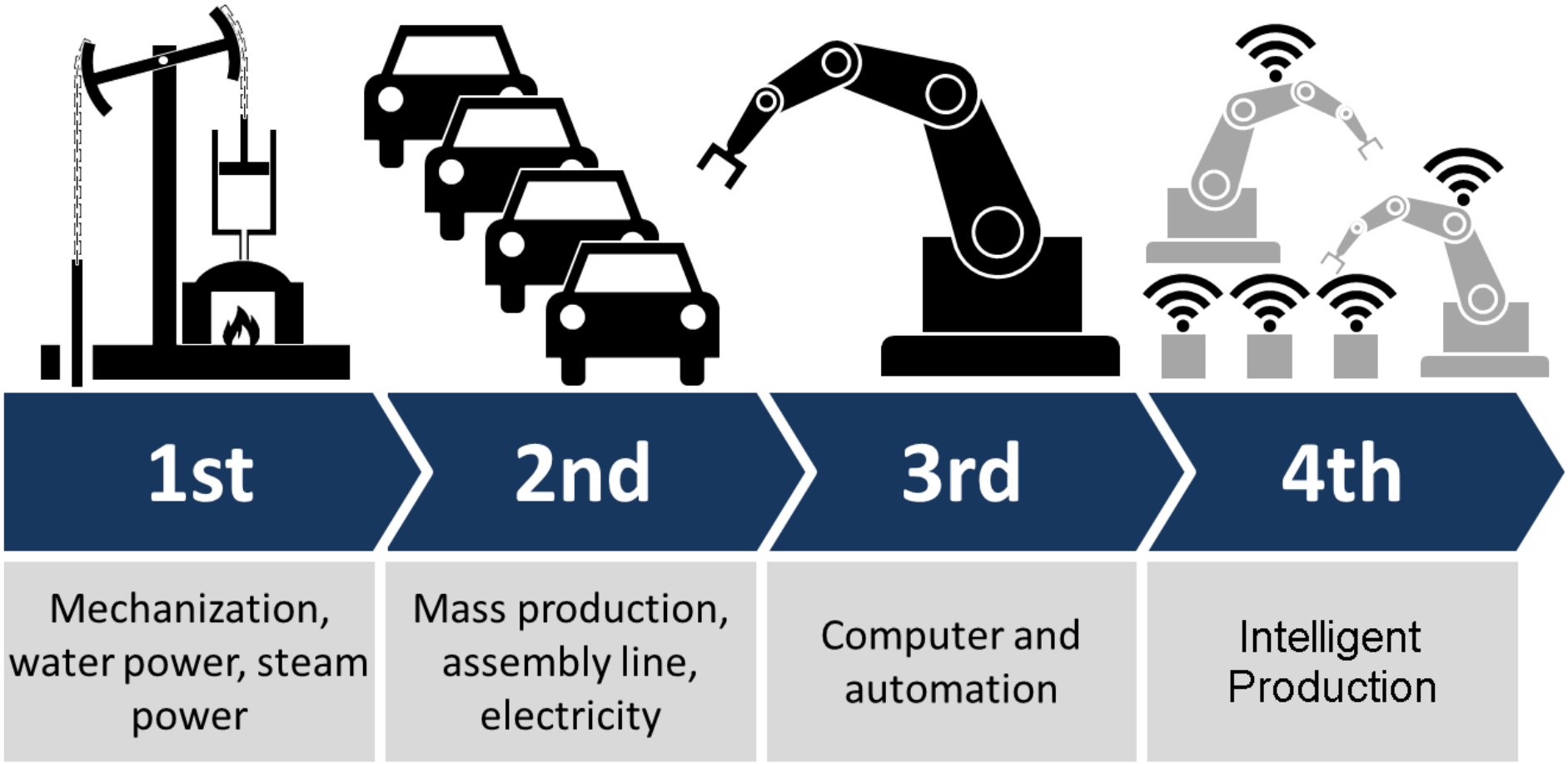


image source: modified from http://en.wikipedia.org/wiki/File:Industry_4.0.png [3]

Involved Technologies

- Cyber-Physical Systems: deep connection between physical and software systems, often networks of interacting elements. [5]

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- Computational Intelligence and Optimization [1, 9, 10]: automatic intelligent decisions, automated planning, scheduling, design, management, ...

Section Outline

What is optimization? [1, 9, 11]

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What is the cheapest way to get from Hefei to Beijing?

What is optimization? [1, 9, 11]

What is the fastest way for our team to finish all the work?

What is optimization? [1, 9, 11]

How can I package these products using the fewest boxes?

What is optimization? [1, 9, 11]

What is the fastest way to lose 20kg?

What is optimization? [1, 9, 11]

Definition (Optimization Problem: Economical View)

An optimization problem is a situation which requires deciding for one choice from a set of possible alternatives in order to reach a predefined/required benefit at minimal costs.

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Definition (Optimization Problem: Simplified Mathematical View)

Solving an optimization problem requires finding an input value $y^\star \in \mathbb{Y}$ from a set $\mathbb{Y}$ of allowed values for which a mathematical function $f : \mathbb{Y} \mapsto \mathbb{R}$ takes on the smallest possible value.

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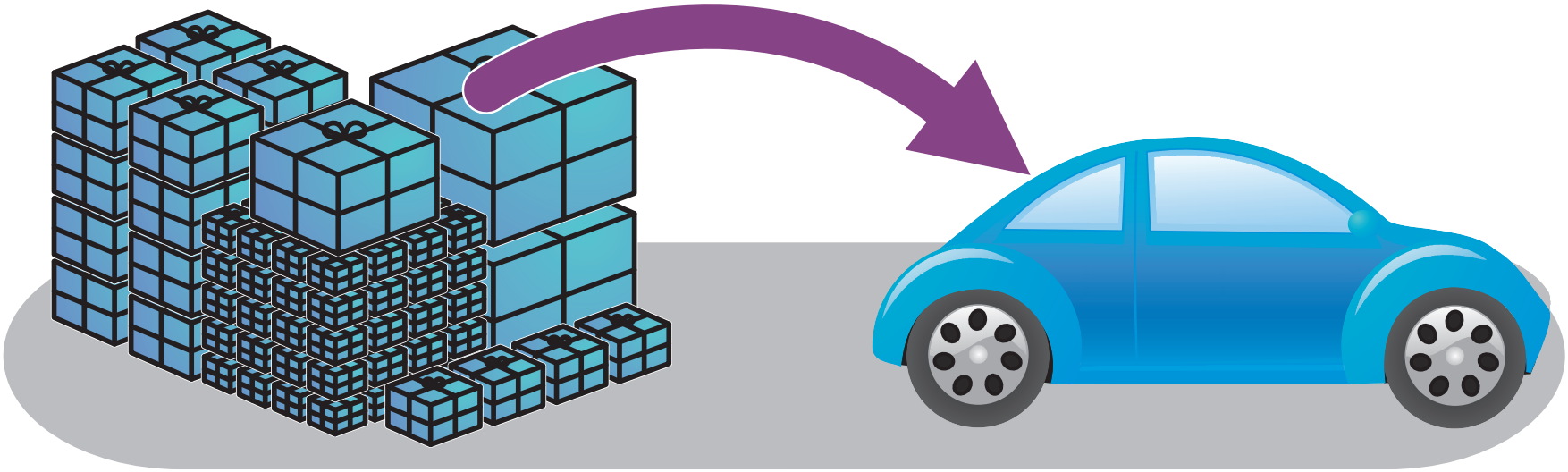
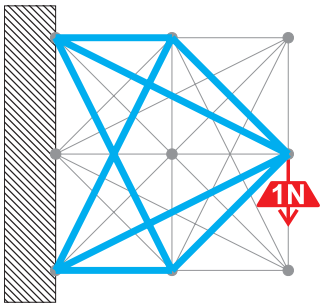
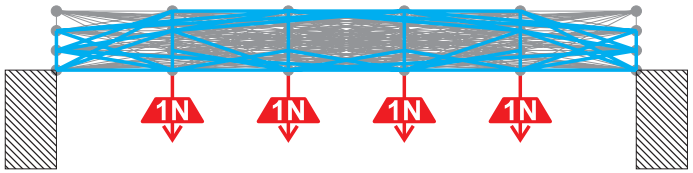
  - Find the *shortest* tour for a salesman to visit a certain set of cities
  - I need to transport n items from here to another city but they are too big to transport them all at once. How can I load them best into my car so that I have to travel back and forth the least times?

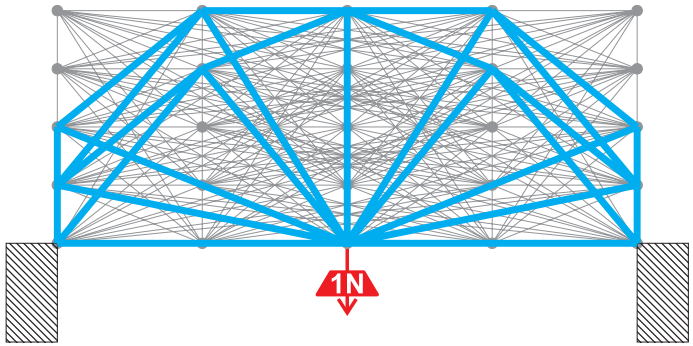


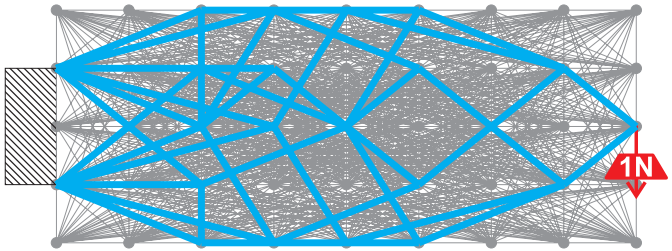
Optimization

- Many questions in the real world are *optimization problems*, e.g.,
  - Find the *shortest* tour for a salesman to visit a certain set of cities
  - I need to transport n items from here to another city
  - How can I construct a truss which can hold a certain weight with at most a certain amount of iron?









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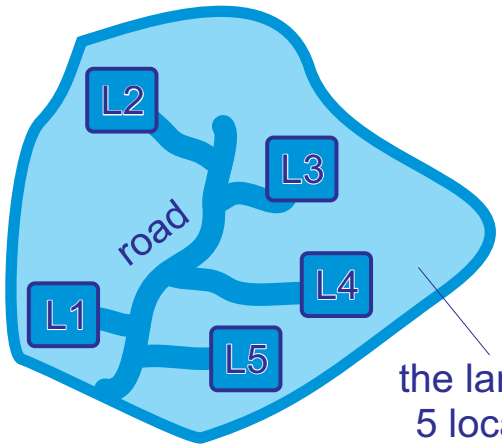
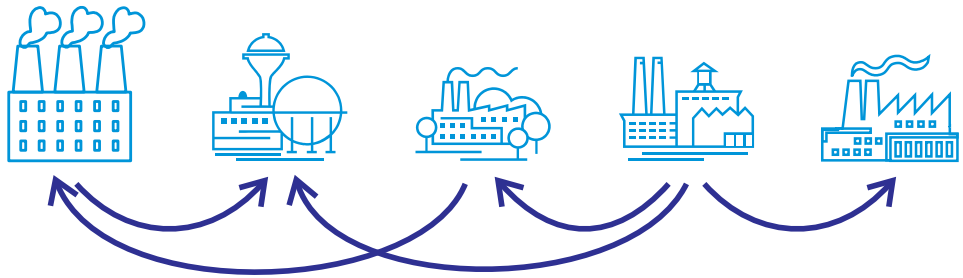
  - Find the *shortest* tour for a salesman to visit a certain set of cities
  - I need to transport n items from here to another city
  - Construct a truss which can hold a certain weight
  - I want to build a large factory with n workshops. I know the flow of material between each two workshops and now need to choose the locations of the workshops such that the overall running cost incurred by material transportation is *minimized*.



the land with
5 locations



5 workshops and goods flows betwee them
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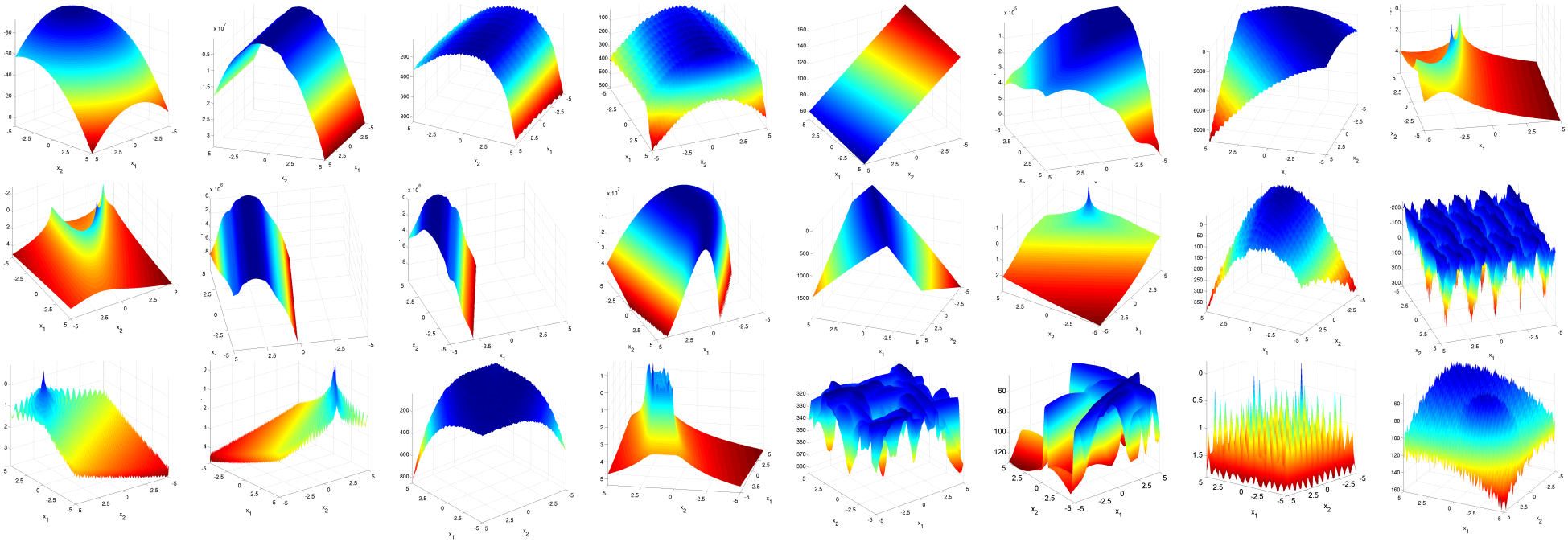
  - I need to transport n items from here to another city
  - Construct a truss which can hold a certain weight
  - Assign workshops to locations
  - Find the minima of complex, multi-dimensional mathematical formulas



Transportation Planning

- Let us now look at a more complex example from the field of transportation planning.

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- This was an actual project for a major German logistics company

Logistic Planning: Task

- Build a system which tells a logistics company what it needs to do to fulfill all transportation orders at minimum costs. [12–16]

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- What does this mean?

Logistic Planning: Task

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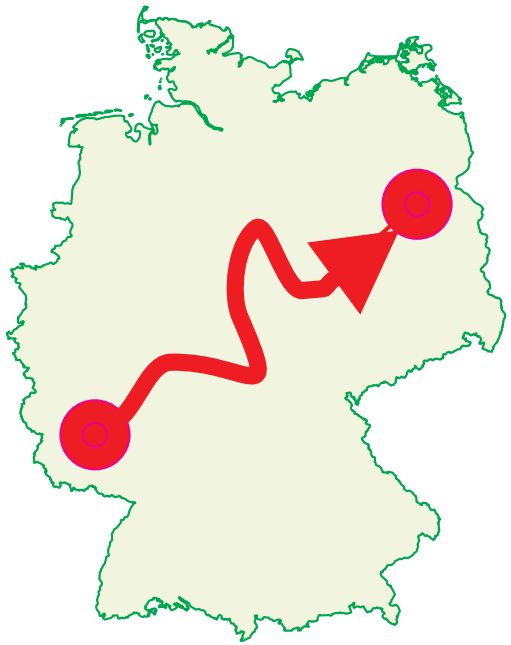
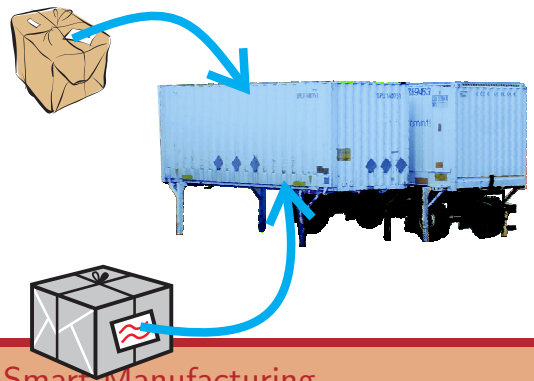
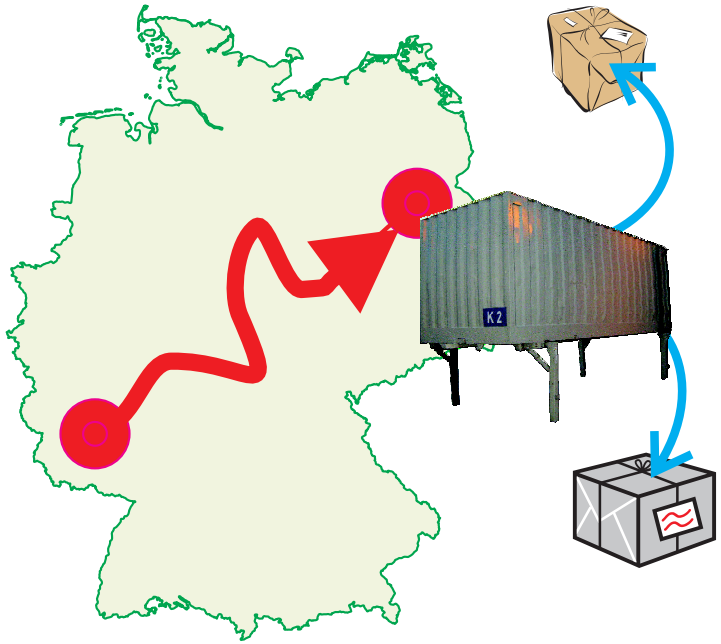
  1. Find routes on the map



Logistic Planning: Task

- Build a system which tells a logistics company what it needs to do to fulfill all transportation orders at minimum costs. [12–16]
  1. Find routes on the map and assignments of orders to containers





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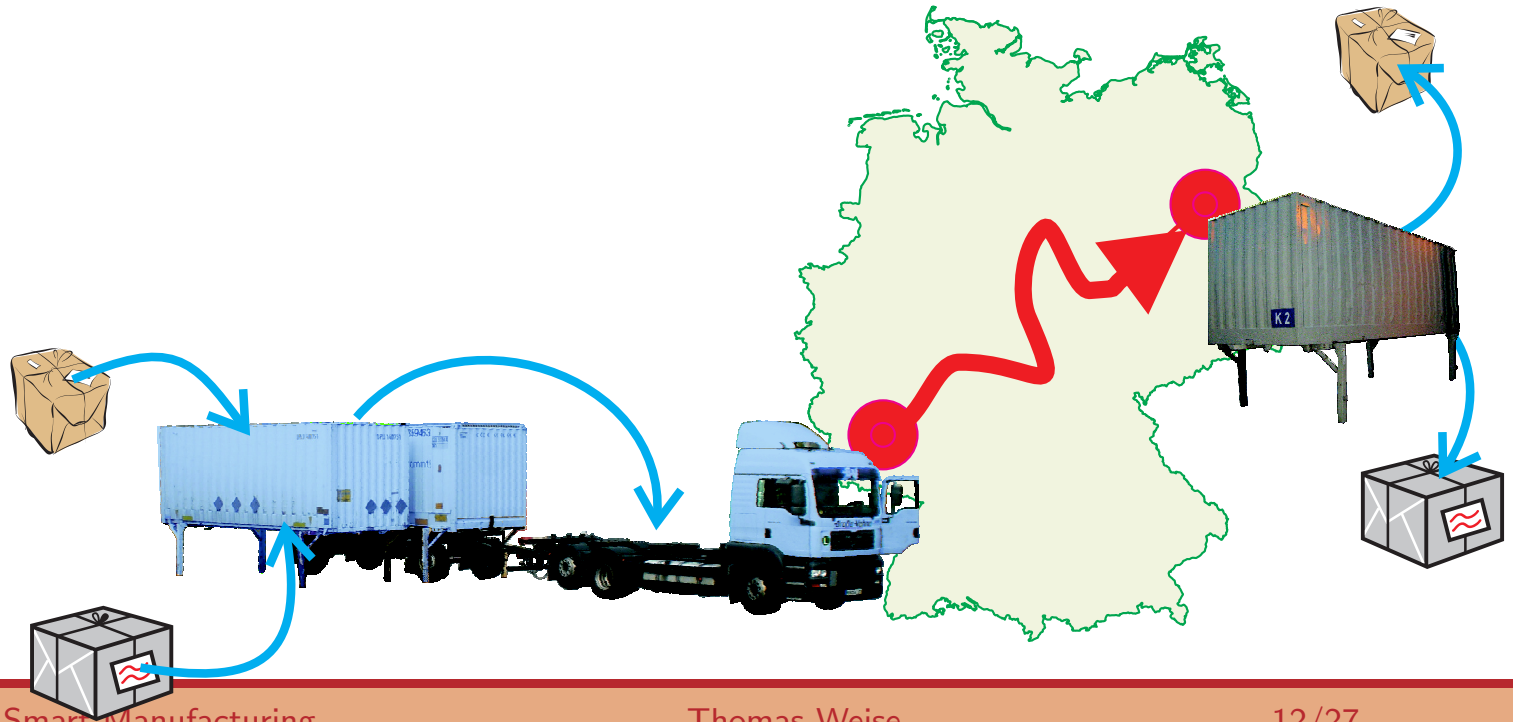
  1. Find routes on the map and assignments of orders to containers and containers to trucks



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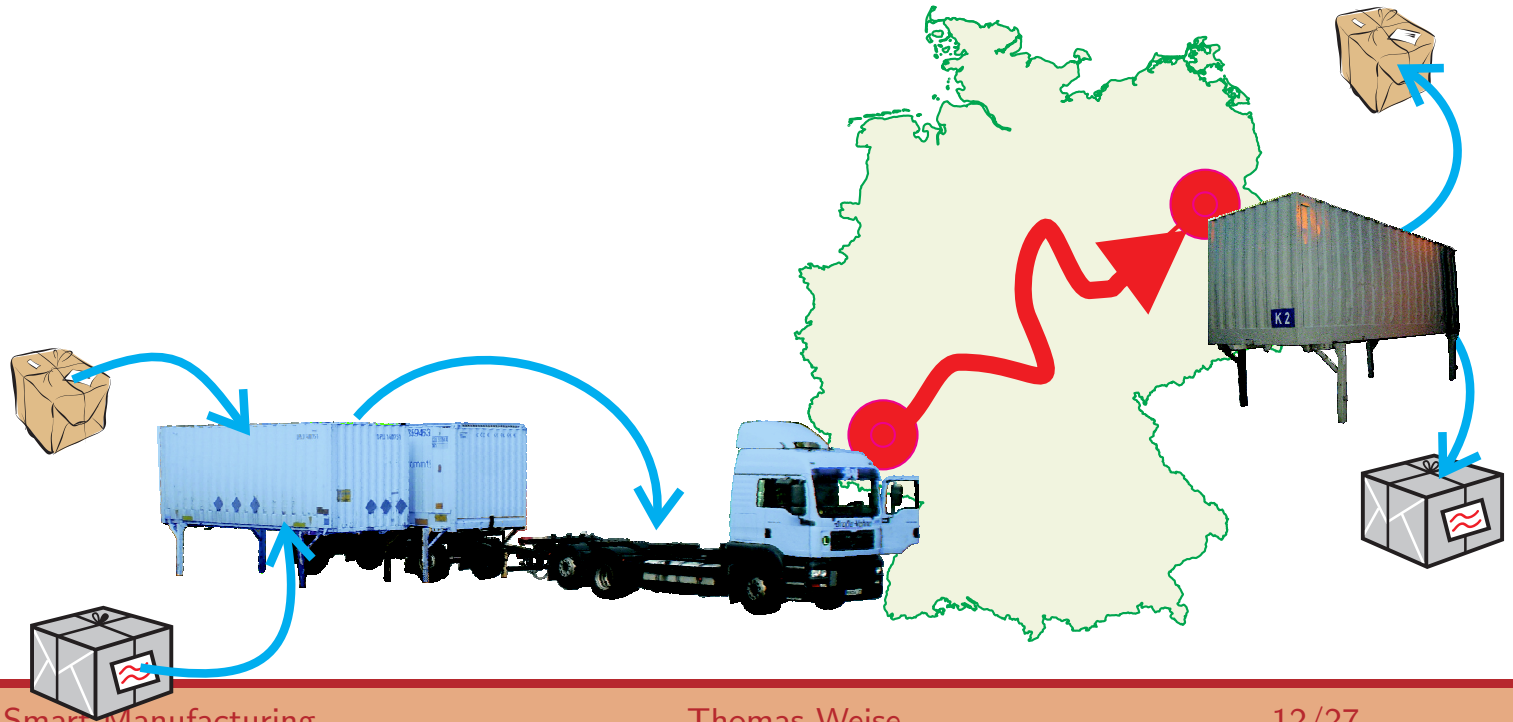

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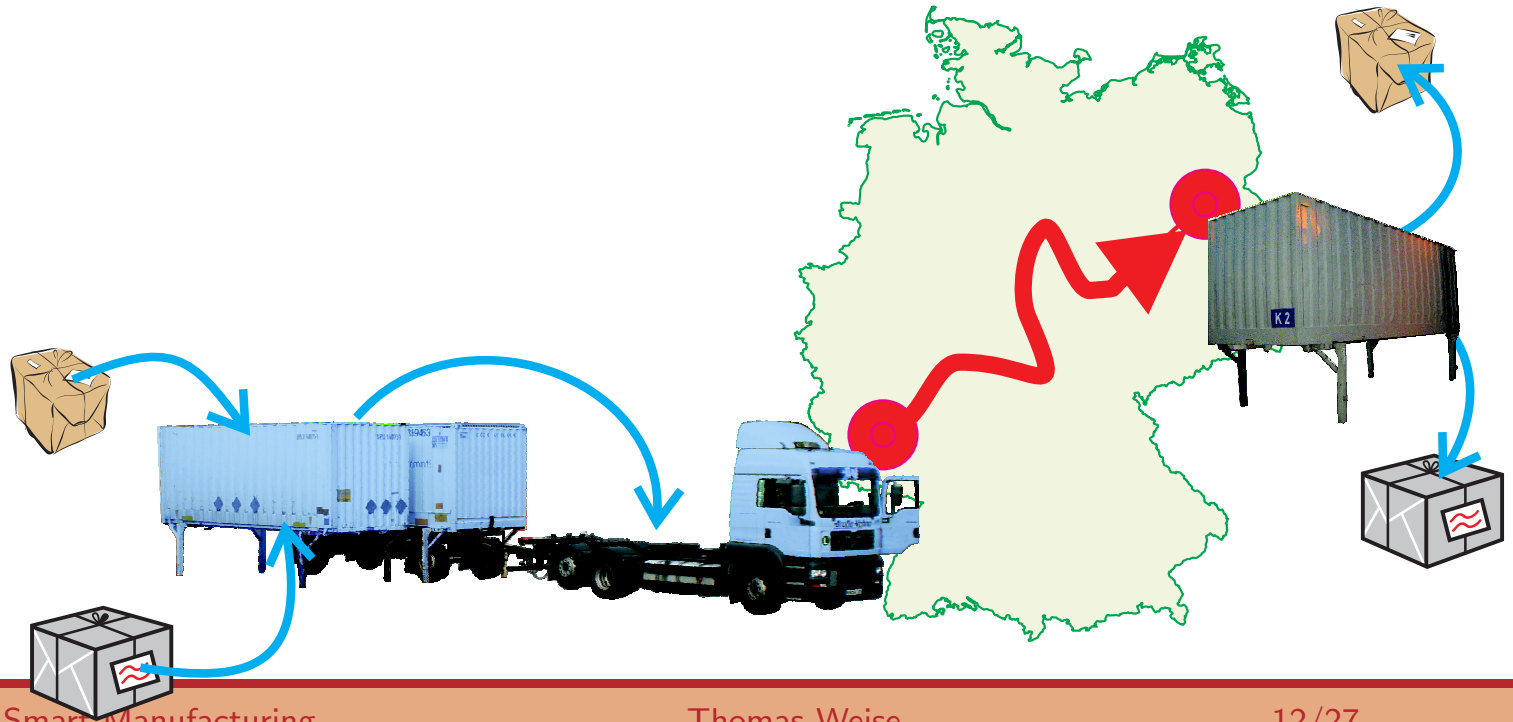
  1. Find routes on the map and assignments of orders to containers and containers to trucks/trains which minimize the undelivered orders



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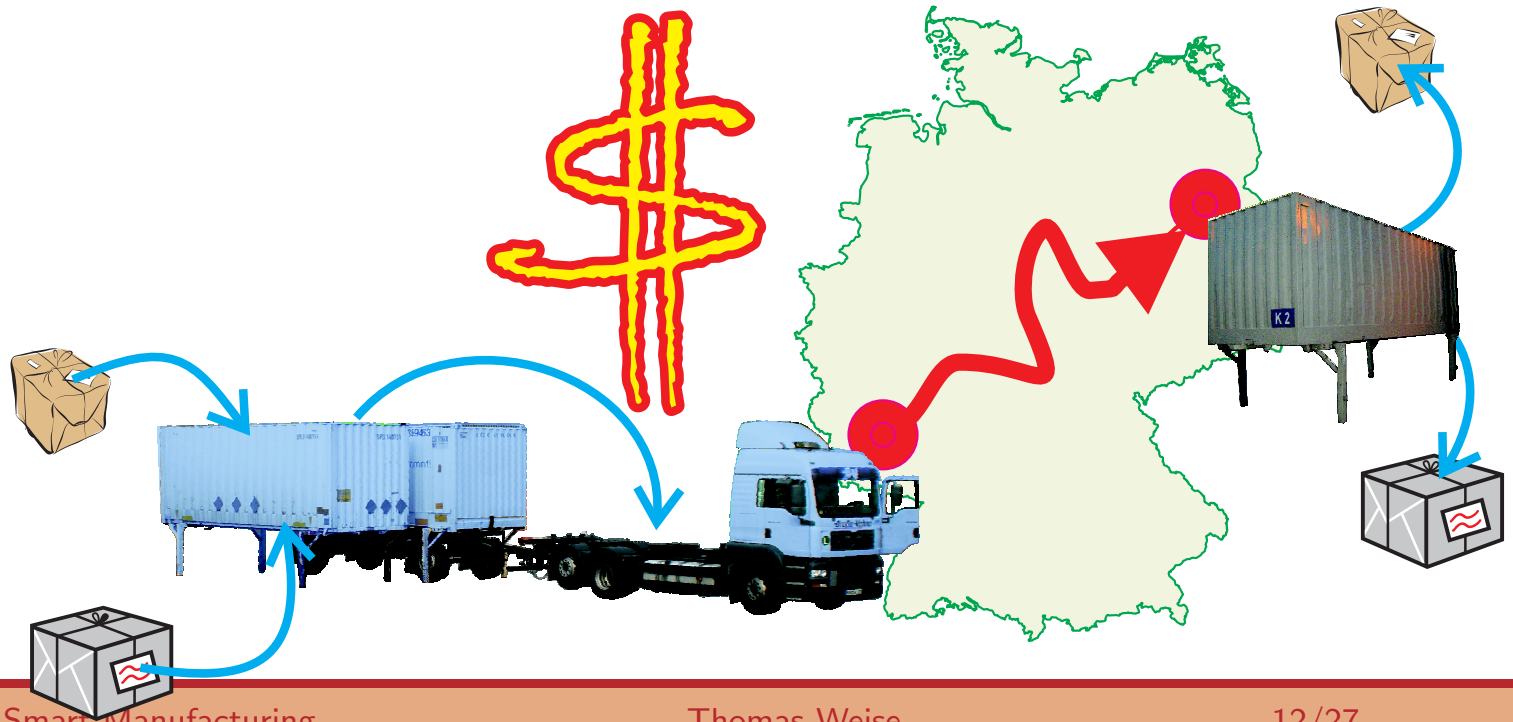

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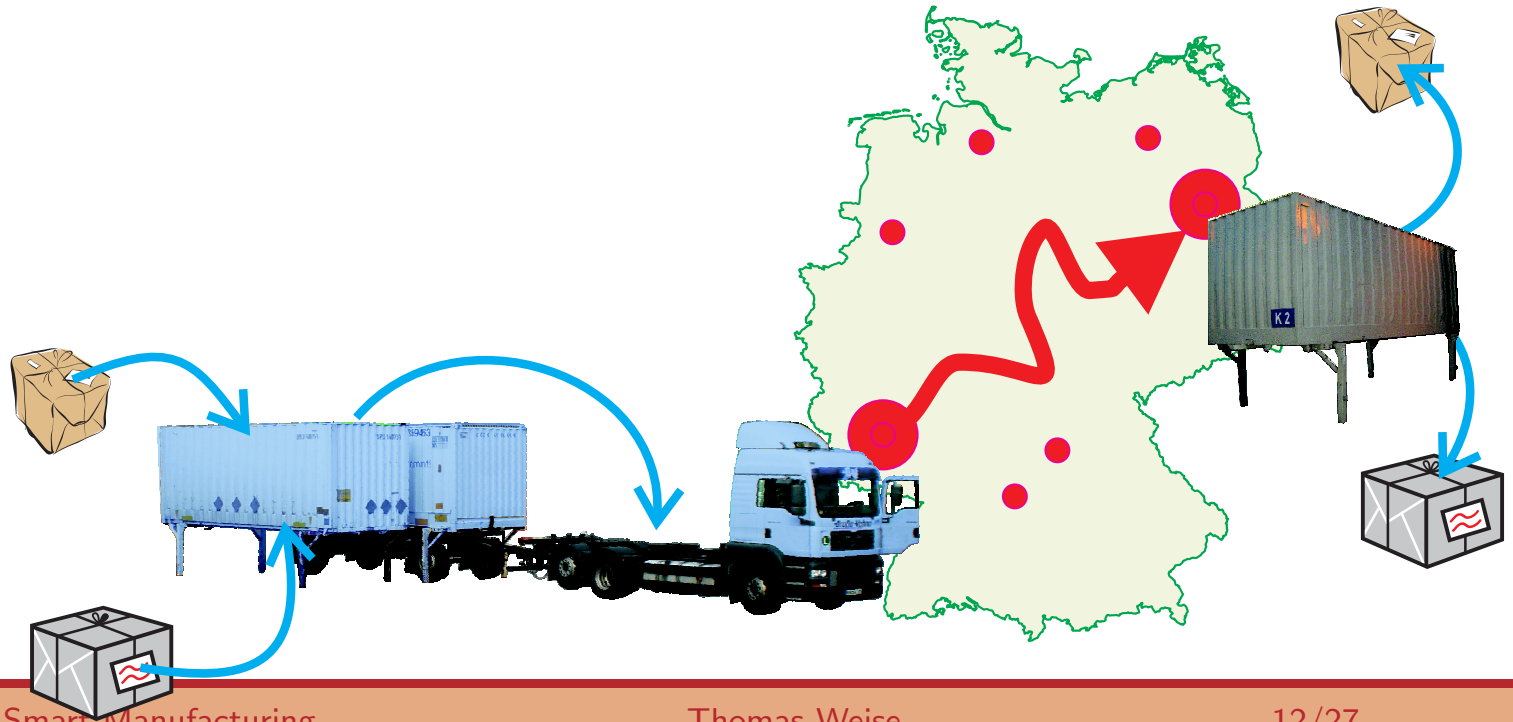

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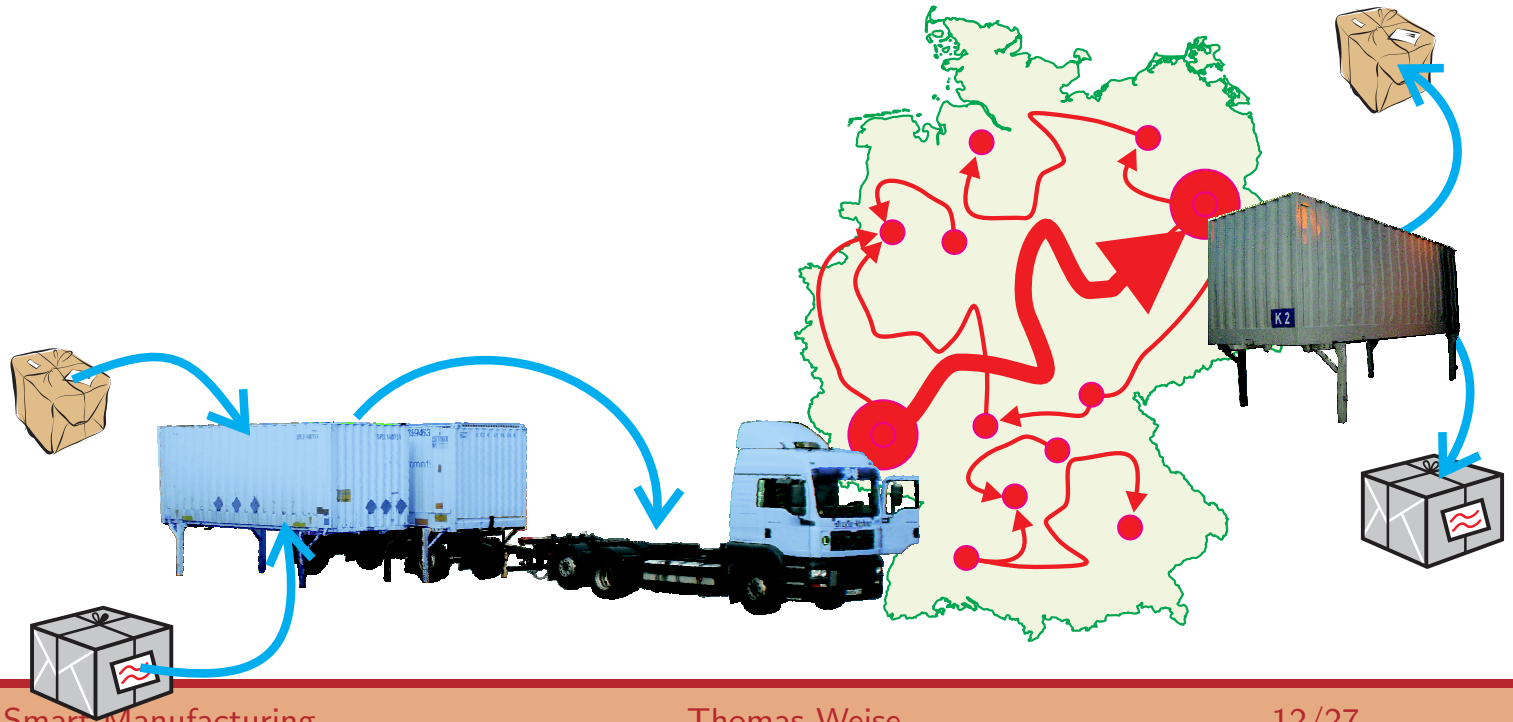

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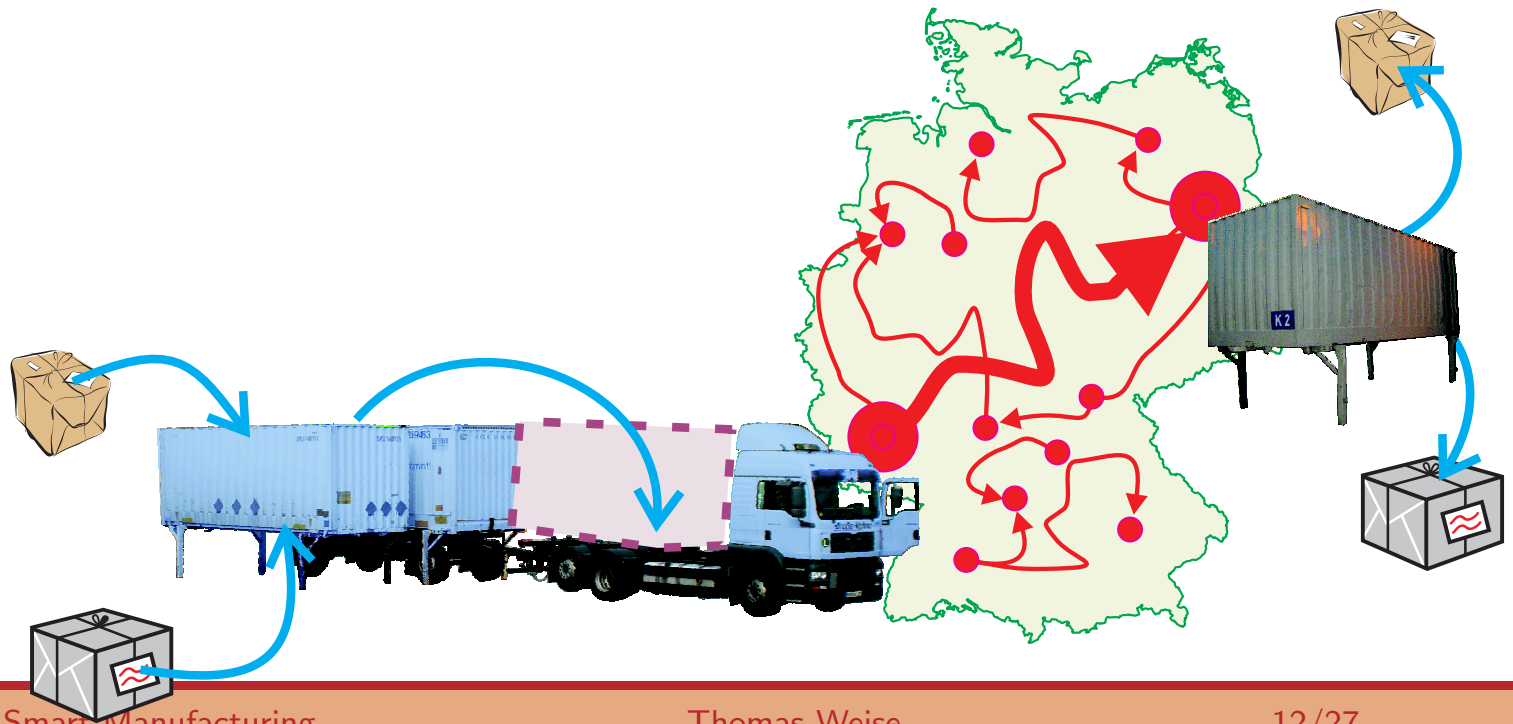

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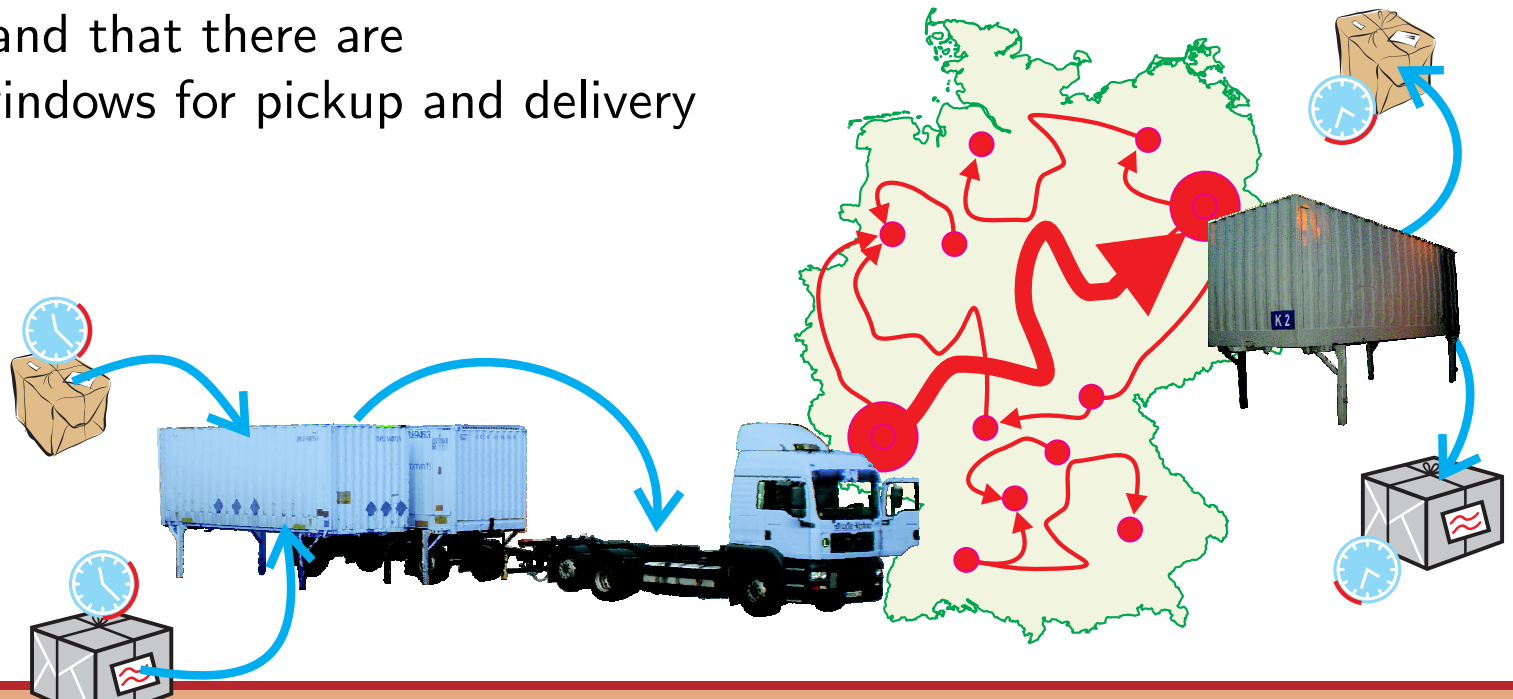

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  6. Time limit for optimization: 1 day

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- With an optimization algorithm, we can get better solutions than that.
- In this course, you will learn how we can do such a thing.

Relationship with Smart Manufacturing

- So how is all of this related to smart manufacturing?

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- No enterprise can waste money

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- No enterprise can waste money or time

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- An enterprise should want to have software that can automatically make good suggestions, which can save costs and resources for the daily operations, the long term planning, and/or even its product/organizational development.
- All kinds of the previously mentioned problems can occur in manufacturing.

Relationship with Smart Manufacturing

- So how is all of this related to smart manufacturing?
- No enterprise can waste money or time or material or energy or any other resource.
- An enterprise must try to make decisions which are optimial from the perspective of cost and resource consumption.
- An enterprise must strive to improve its processes and products.
- An enterprise should want to have software that can automatically make good suggestions, which can save costs and resources for the daily operations, the long term planning, and/or even its product/organizational development.
- All kinds of the previously mentioned problems can occur in manufacturing.
- For example, logistics exist inside and outside a company, and even on the factory floor!

Examples from Smart Manufacturing

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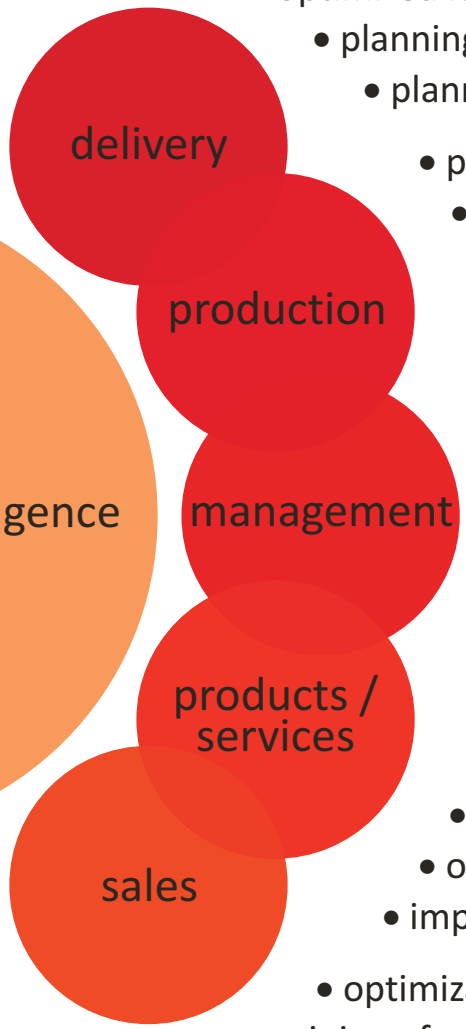

- optimized logistics (business-to-customer)
- planning and scheduling of maintenance visits
- planning and scheduling of supply visits

- production planning and scheduling
- optimized assignment of jobs/orders to machines
- optimization of production processes
- optimization of stock-keeping
- optimization of intra-enterprise logistics
- optimization of supply chains
- optimization of factory layouts and intra-factory logistics

- scheduling of employee work
- optimal assignment of employees to tasks or customers
- optimized locations for new branch offices (based current or predicted future customers)

- optimization of product design
- optimization of product feature configuration
- optimization of service offers
- improved tailoring of products/services to customers

- optimization of pricing and offers
- mining of customer data for targeted offers

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  1. Developing and implementing a good algorithm that can solve the problem at hand and
  2. integrating this implementation into the existing software ecosystem.
- We focus only on the first of the two issues: optimization algorithms and their implementation.

Section Outline

Exact vs. Heuristic Algorithms

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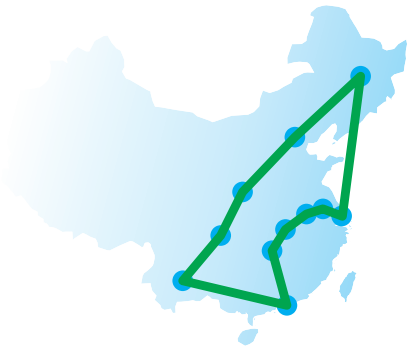

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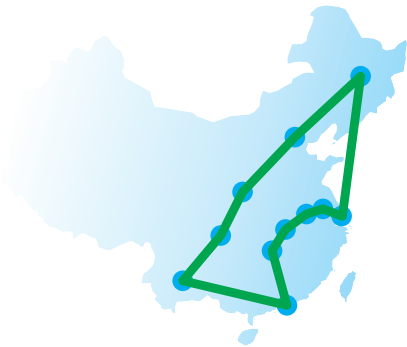

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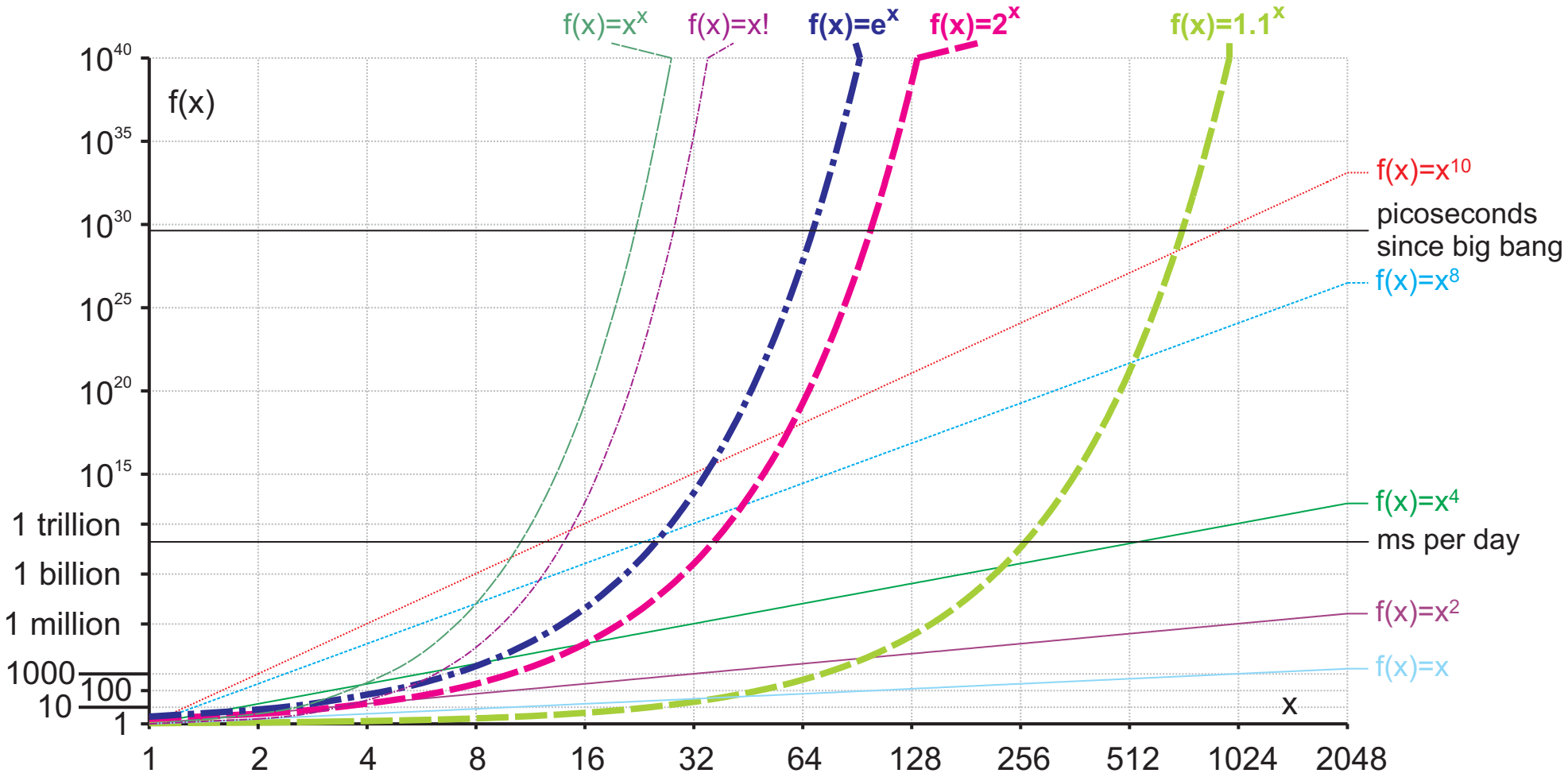

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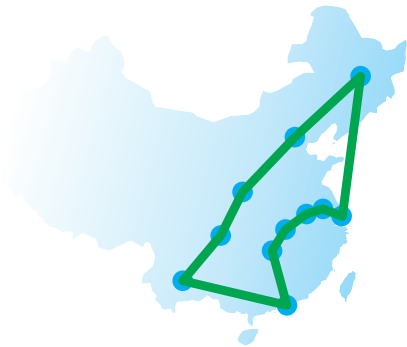

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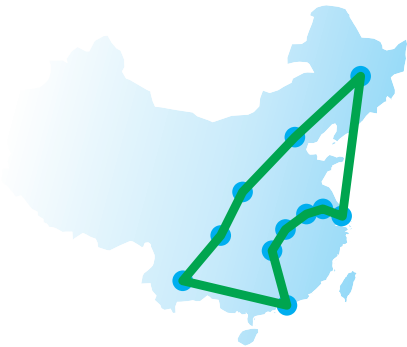

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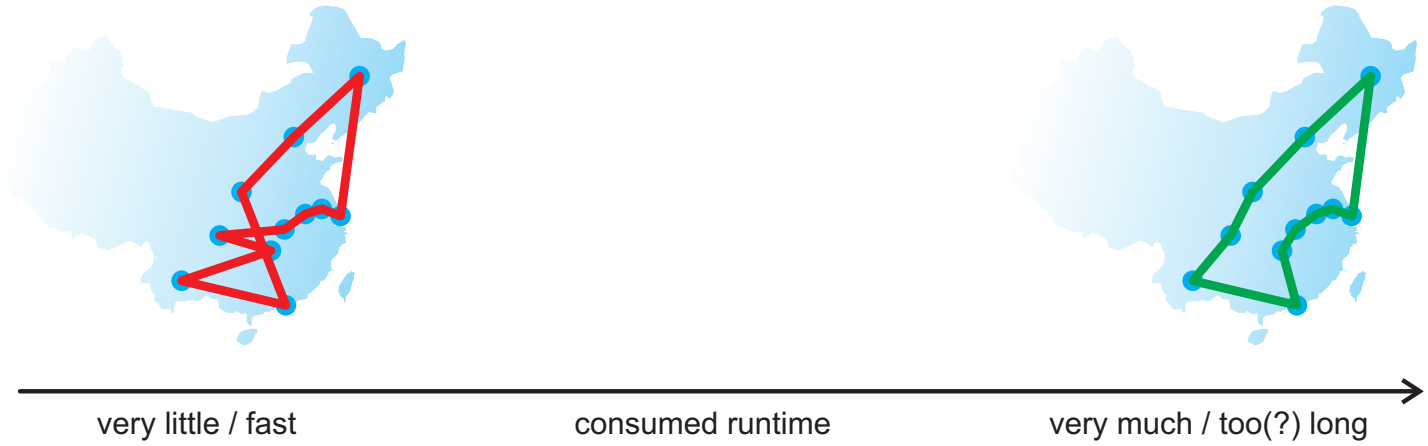

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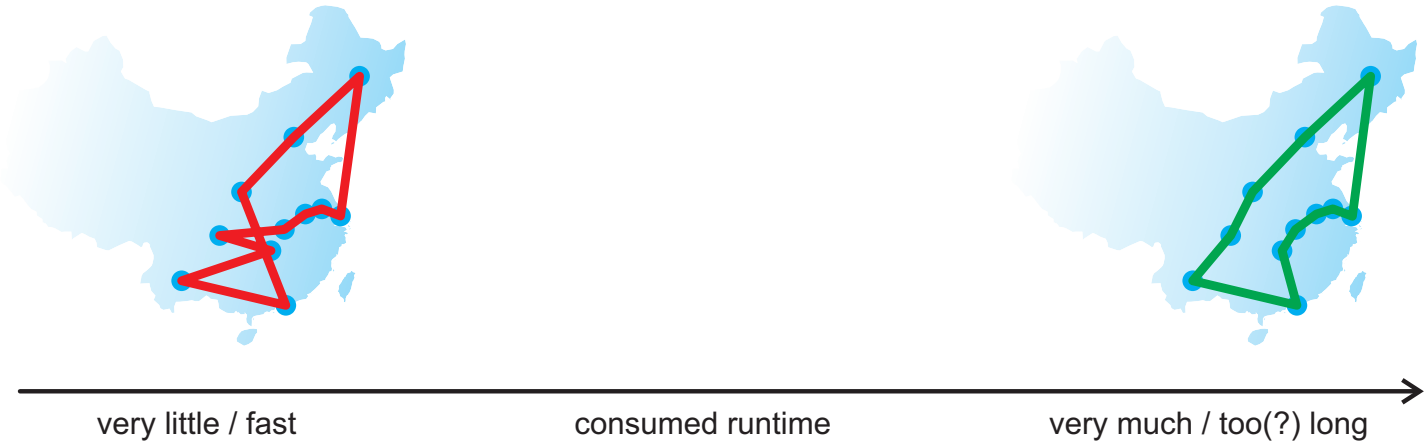

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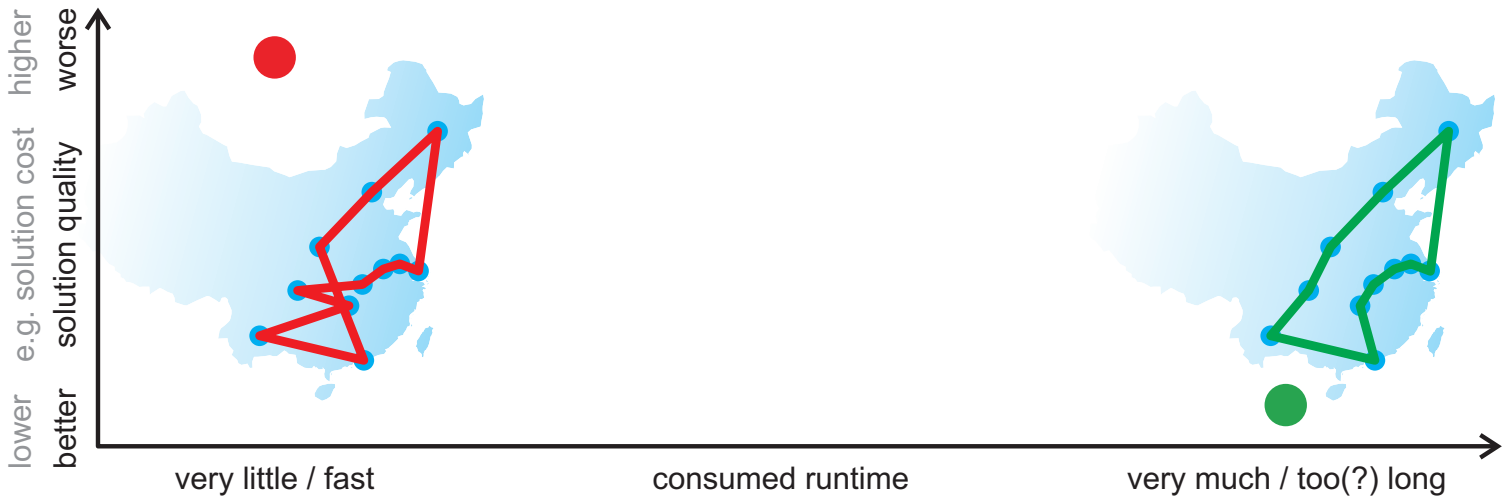

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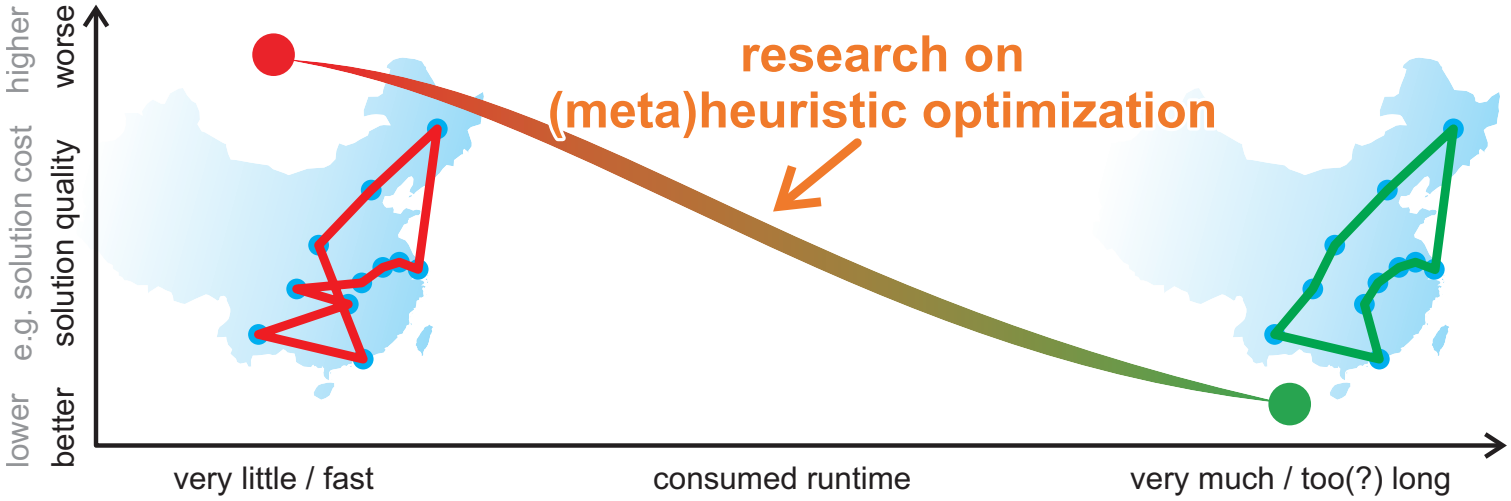

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- We will try to get a good perspective and understanding of the very basics needed to navigate in the domain of optimization.
- The goal is to be able to recognize and identify optimization problems as they occur in many fields, especially in Intelligent Manufacturing scenarios, and to develop basic algorithms to solve them.

谢谢

Thank you

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Caspar David Friedrich, “Der Wanderer über dem Nebelmeer”, 1818
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