Metaheuristic Optimization

21. Representations

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Outline

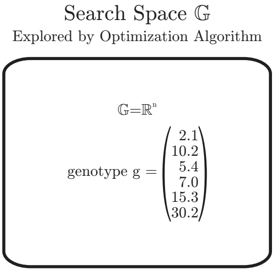
1. Introduction
2. Real-World VRP
3. Summary

website

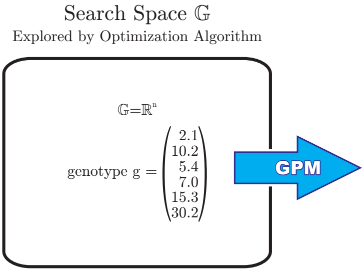
Section Outline

1. Introduction
2. Real-World VRP
3. Summary

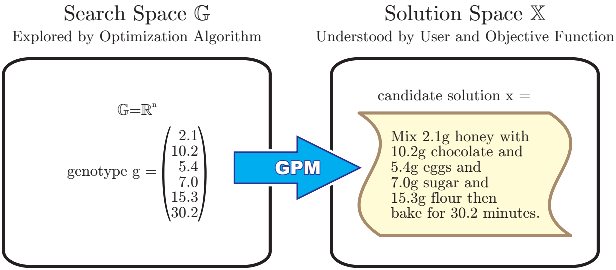
- Search space $\mathbb{G}$ (genome, contains genotypes)



- Genotype-phenotype mapping (gpm) translate from $\mathbb{G}$ to $\mathbb{X}$

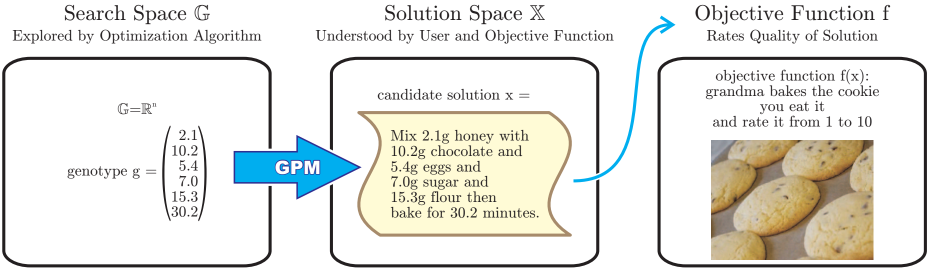


- Genotype-phenotype mapping (gpm) translate from $\mathbb{G}$ to $\mathbb{X}$
- Solution space $\mathbb{X}$ (genome, contains phenotypes=candiate solutions)

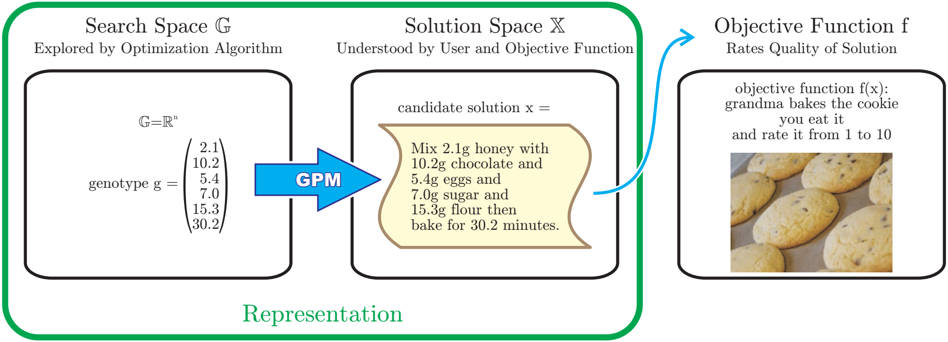


Representation

- f: rates quality of candiate solutions



- f: rates quality of candiate solutions
- Search Space $\mathbb{G}$, genotype-phenotype mapping gpm, and $\mathbb{X}$ $\mathbb{X}$ together are called the *Representation*



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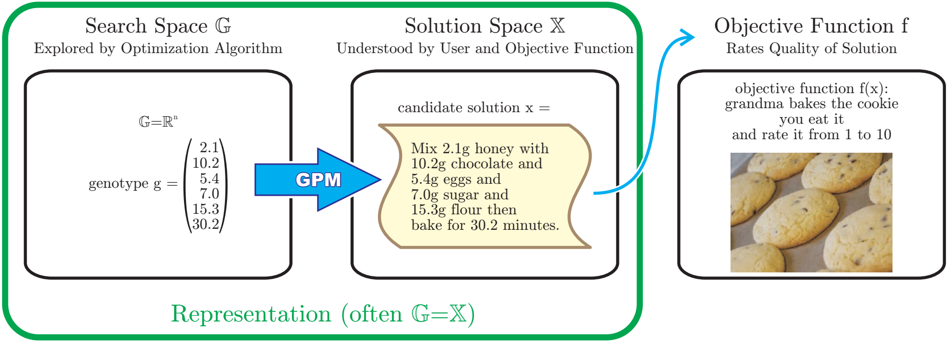
- Genotype-phenotype mapping becomes identity mapping if $\mathbb{G} = \mathbb{X}$



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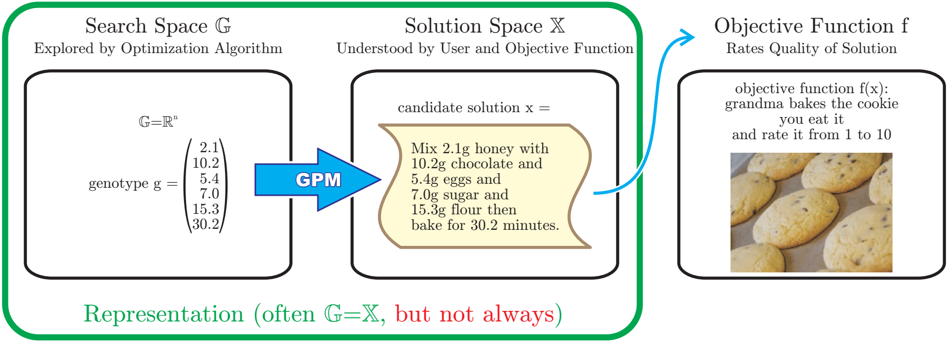

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  - domain-specific search space (+operators)? $\Longrightarrow$ **Representation**

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  - simple search space + "intelligent" GPM? $\Longrightarrow$ **Representation**

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  - domain-specific algorithm?
  - ...

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    - simple search space + "intelligent" GPM? $\Longrightarrow$ **Representation**
    - domain-specific algorithm?
    - ...
- Choice of representation has major impact on quality of results [2–6]

Section Outline

- Finished work contributing to a freight management system [7–11]

Introduction

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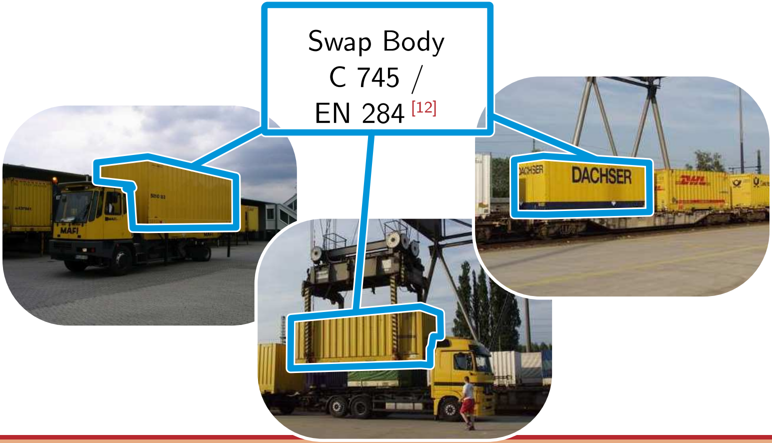
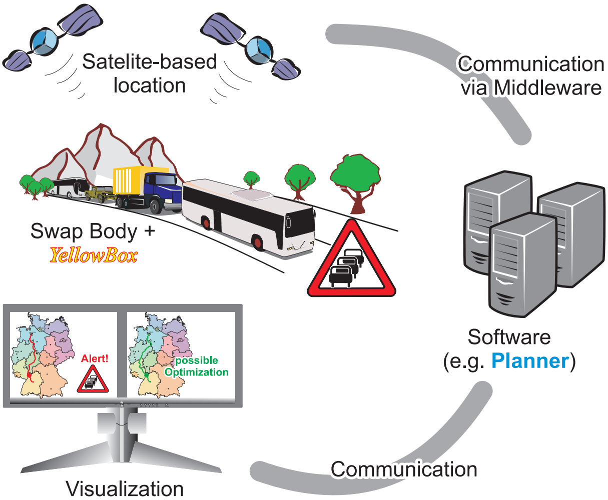


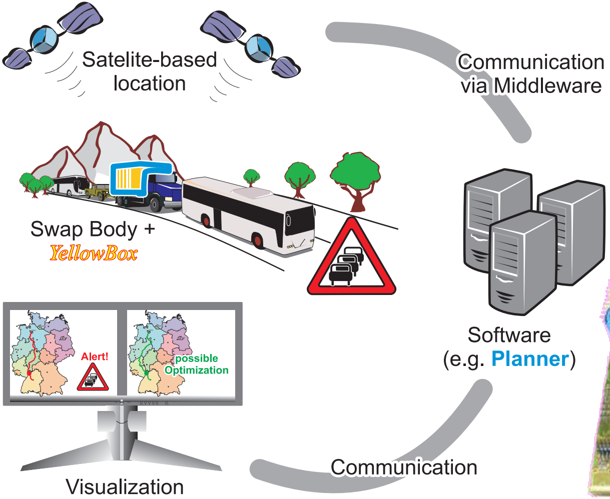
VRP: in.west Project

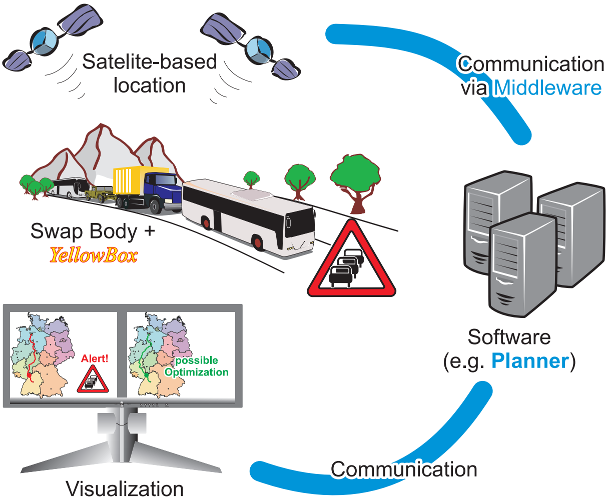


- Holistic Approach

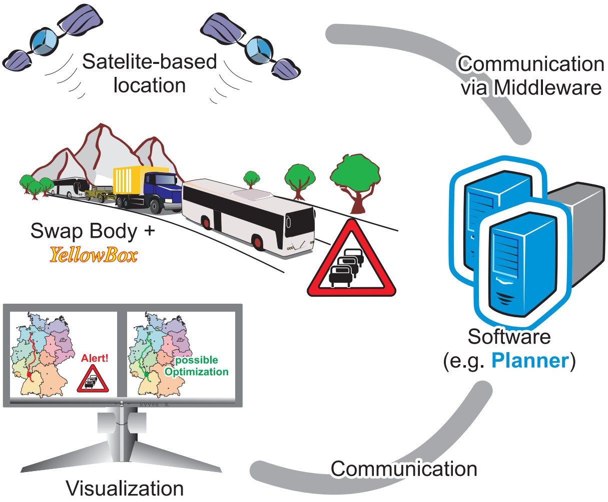
VRP: in.west Project

- Holistic Approach
- Sensor Nodes





- Holistic Approach
- Sensor Nodes
- Middleware



- Holistic Approach
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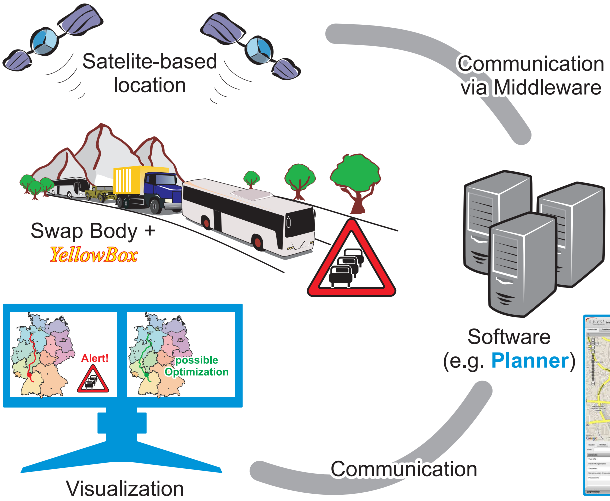
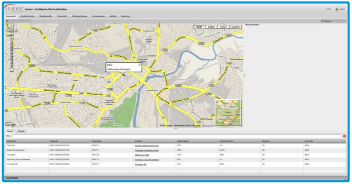
- Middleware
- Transportation Planner

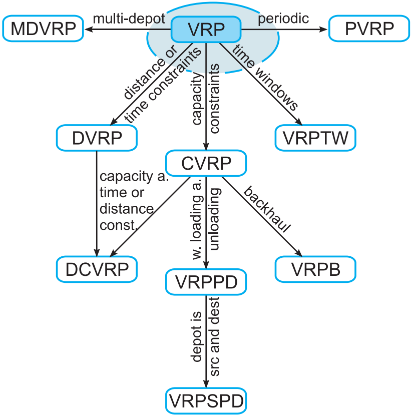


- Holistic Approach
- Sensor Nodes
- Middleware
- Transportation Planner
- Web-based GUI

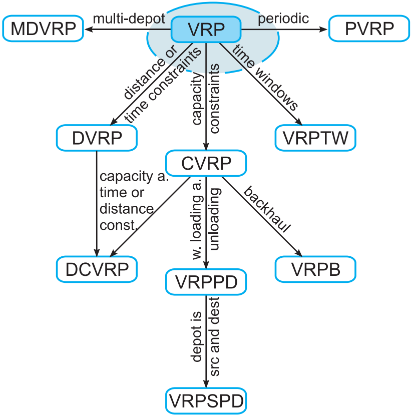


VRP: Situation

- *in.west*: real-world vehicle routing problems of logistics company



- *in.west*: real-world vehicle routing problems of logistics company
- Orders/Containers/Trucks/ Trains/Routes for...



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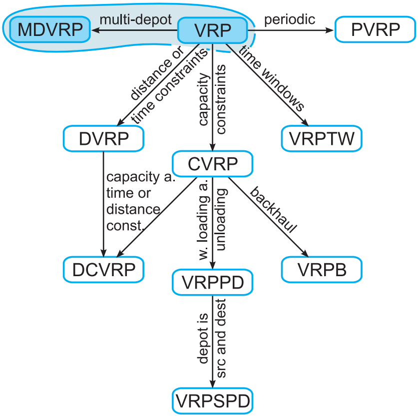

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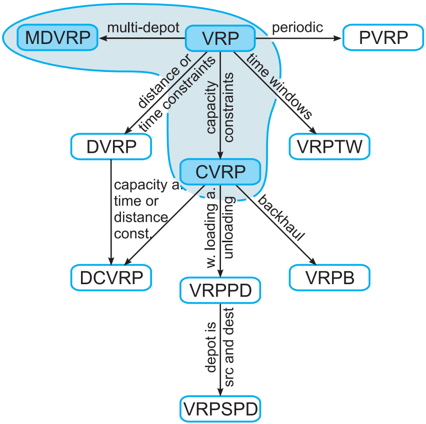

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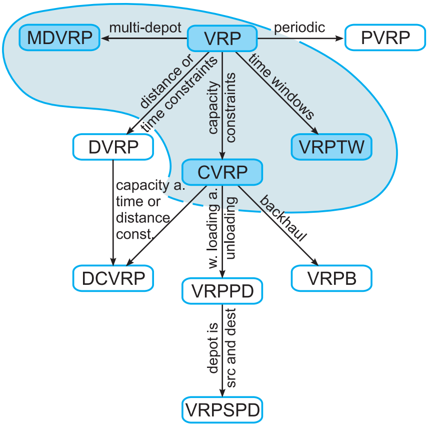
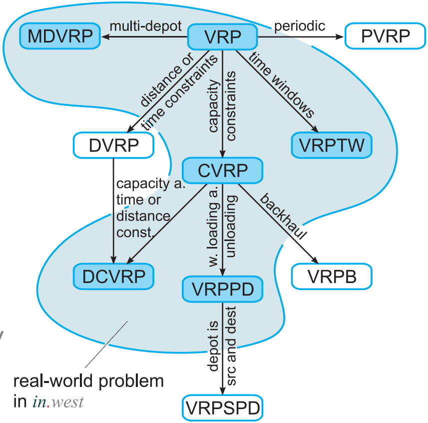


VRP: Situation

- *in.west*: real-world vehicle routing problems of logistics company
- Orders/Containers/Trucks/Trains/Routes for...
- Multiple depots and pickup and delivery locations
- Vehicles (trucks and trains) have (different) capacity limits
- Time windows for pickup and delivery
- Constraints, laws, time limit: 1 day



- What is a solution/plan x for such a scenario?

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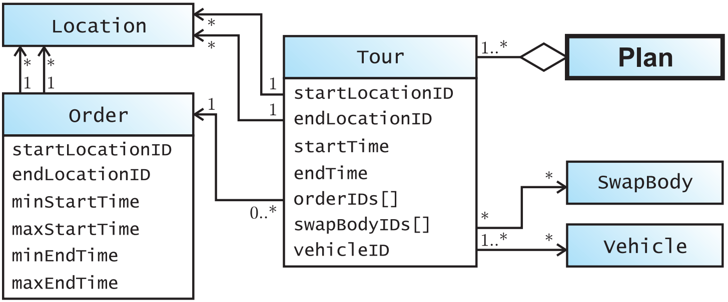
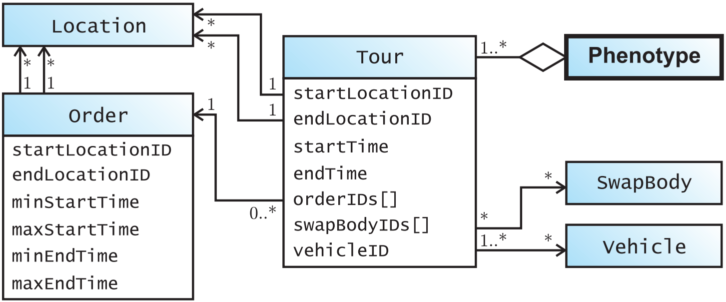
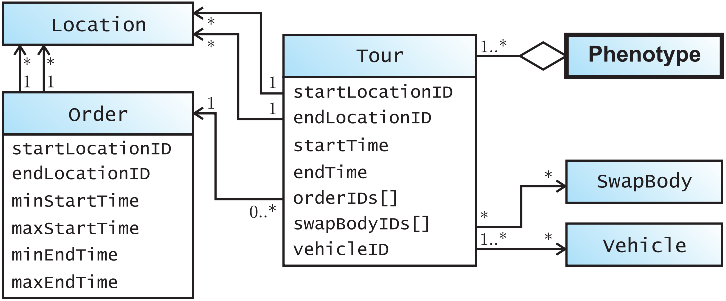


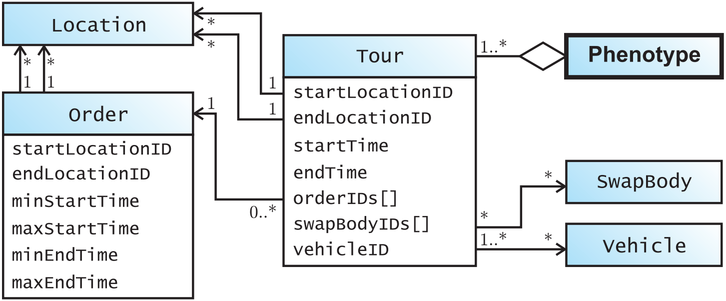
- What is a solution/plan x for such a scenario?
- Solution space $\mathbb{X}$: set of all such solutions



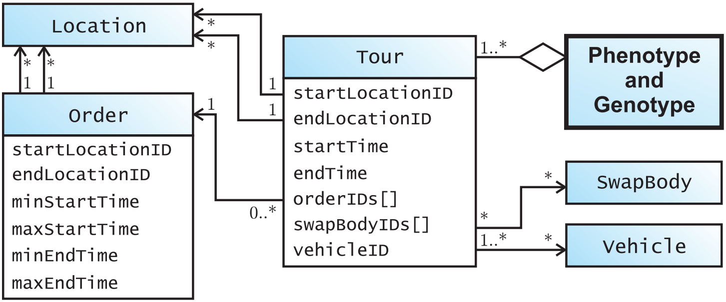
- What is a solution/plan x for such a scenario?
- Search spaces such as integer or bit strings not convenient



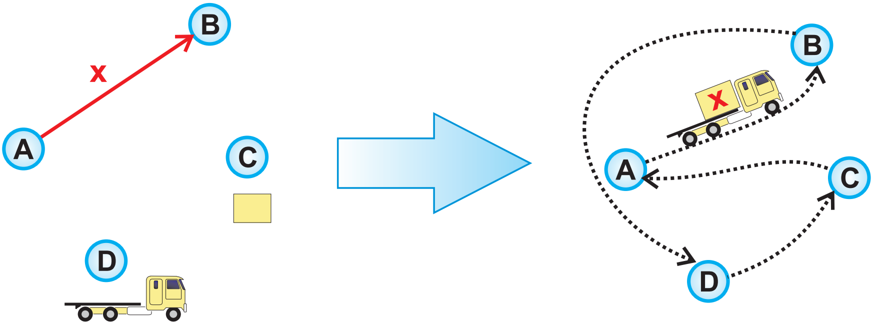
- What is a solution/plan x for such a scenario?
- Search spaces such as integer or bit strings not convenient: encoding, decoding, meaningful modification too complex



- What is a solution/plan x for such a scenario?
- Use solution space $\mathbb{X}$ also as search space $\mathbb{G}$

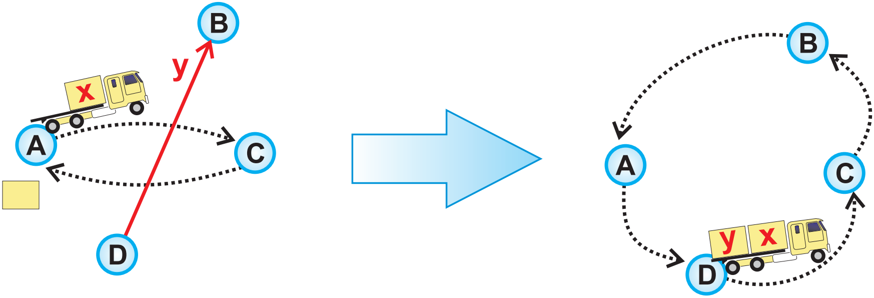


- Mutation 1: Add new tour for undelivered freight to plan

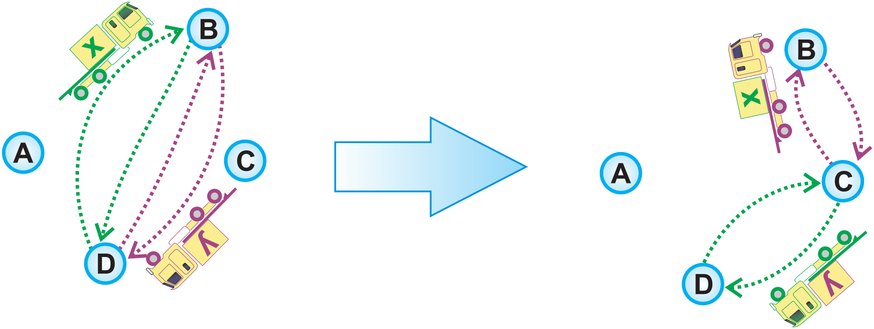


VRP: Representation (Operators)

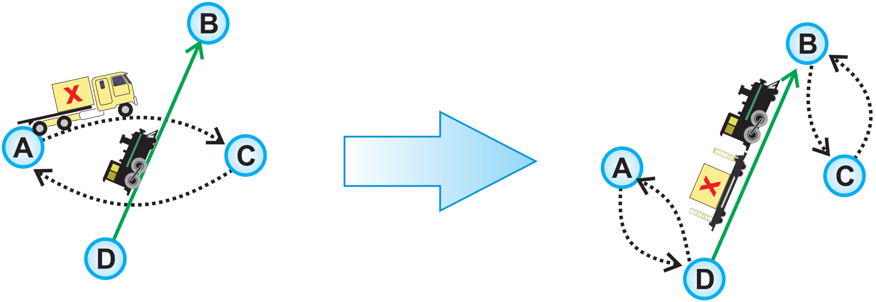
- Mutation 2: Integrate delivery in existing tour



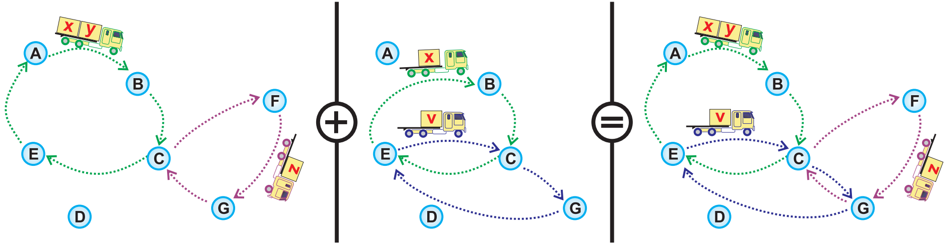
- Mutation 3: Freight exchange / Truck-meets-Truck



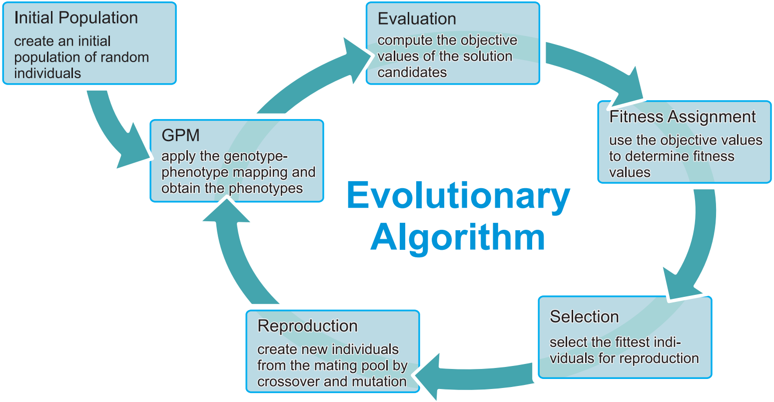
- Mutation 4: Utilize trains with fixed schedules



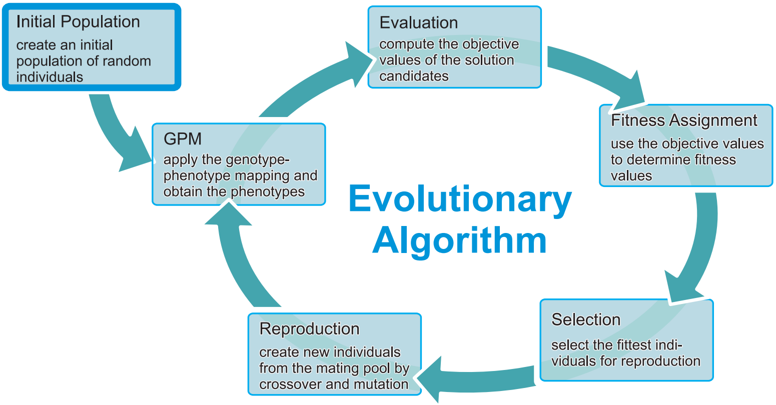
- Crossover 1: Join compatible tours



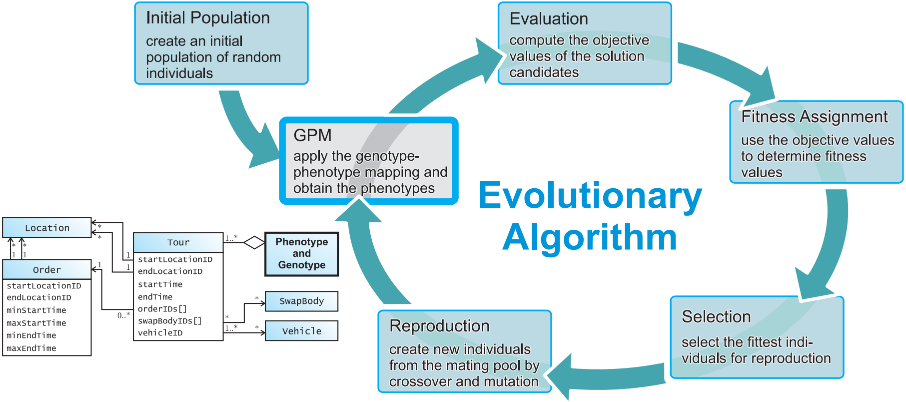
- Optimization method: Evolutionary Algorithm [13]



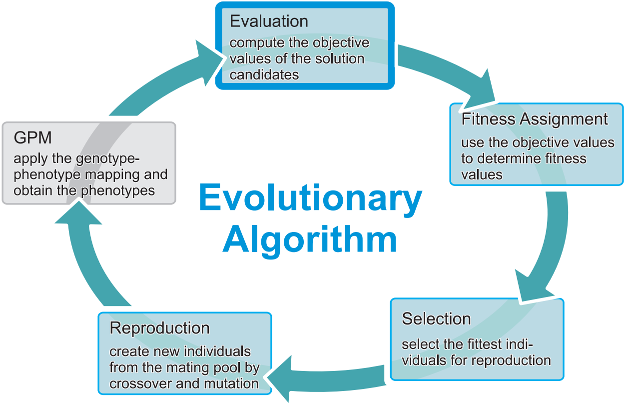
- Initialization: random but *valid* plans that fulfill one randomly chosen task each



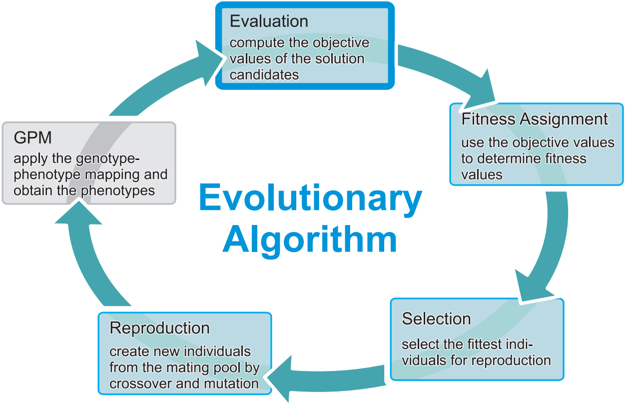
- Transportation Plan = phenotype x = genotype $g \Rightarrow$ no genotype-phenotype mapping necessary



- Criteria: $\underbrace{\text{no. of undelivered orders}}_{\mathbf{f_1}}$

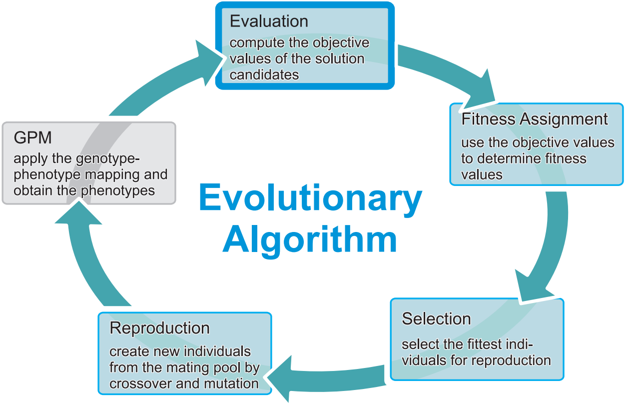


- Criteria: $\underbrace{\text{no. of undelivered orders}}_{\mathbf{f_1}}$, $\underbrace{\text{distance}}_{\mathbf{f_2}}$

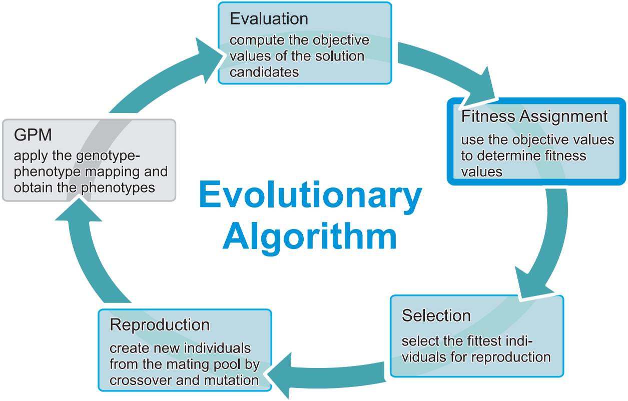


VRP: Solving with EA

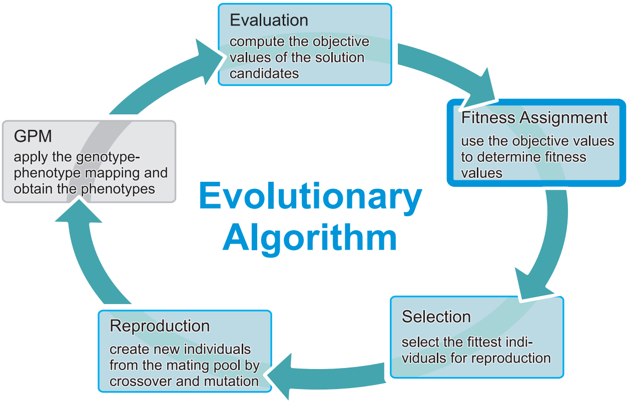
- Criteria: $\underbrace{\text{no. of undelivered orders}}_{\mathbf{f_1}}$, $\underbrace{\text{distance}}_{\mathbf{f_2}}$, $\underbrace{\text{spare capacity}}_{\mathbf{f_3}}$



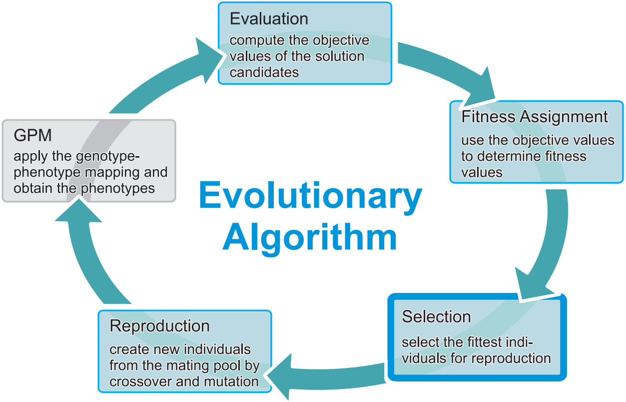
- Pareto Ranking as fitness assignment (see Lesson 15: *Multi-Objective Optimization*)



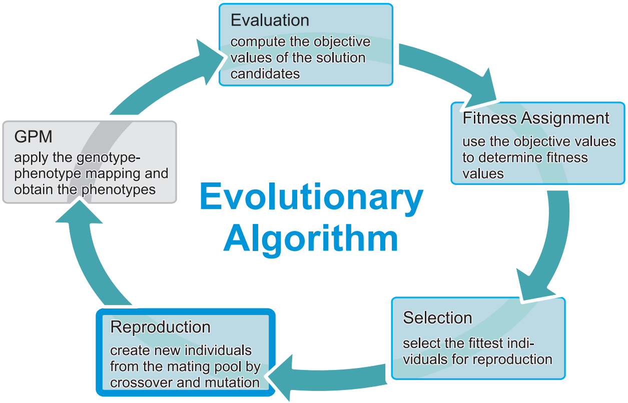
- Pareto Ranking as fitness assignment (see Lesson 15: *Multi-Objective Optimization*)
- Sharing in objective space: increase diversity [13]



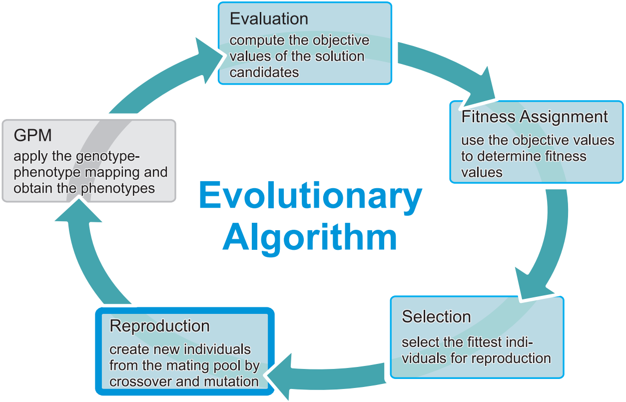
- Selection: tournament selection



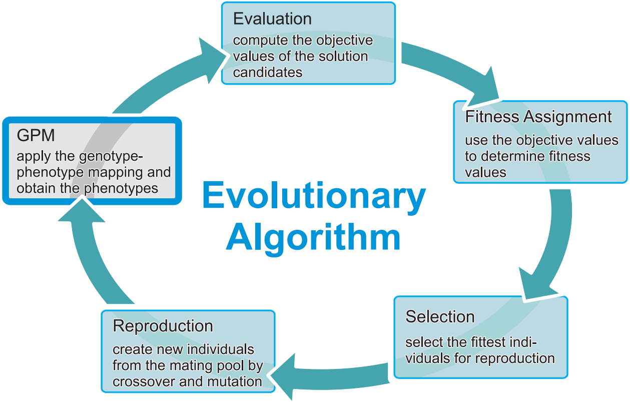
- 16 mutation + 3 crossover constellation-specific operators



- 16 mutation + 3 crossover constellation-specific operators
- Each operator preserves validity; operators randomly chosen for application

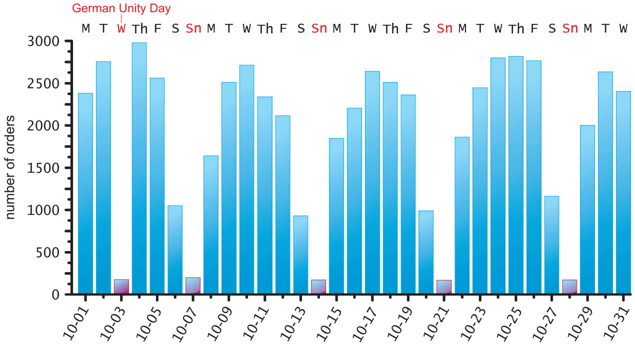


- Cycle starts again



VRP: Experiments

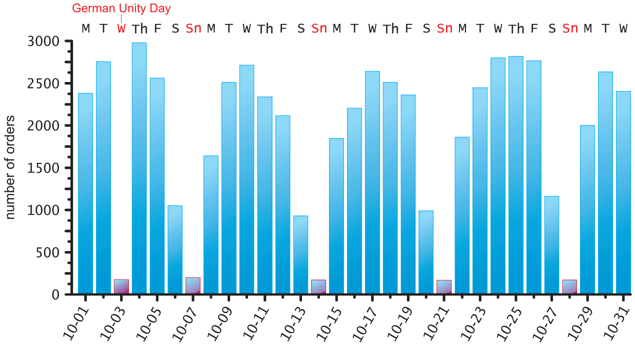
- Original data from project partner



VRP: Experiments

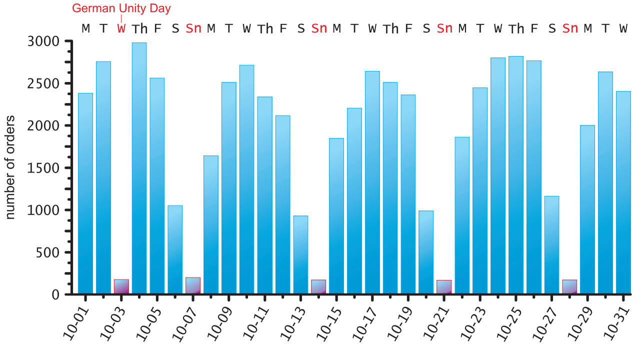
- Original data from project partner

- 4th quarter 2007



- Original data from project partner

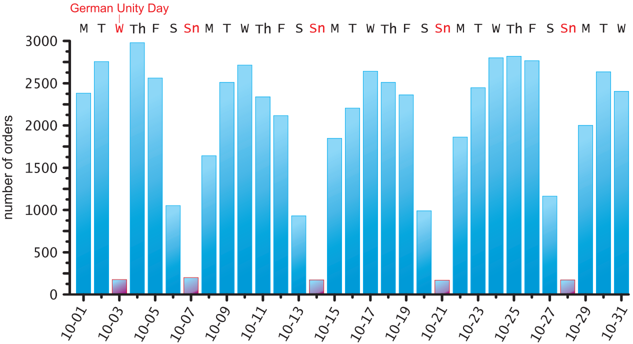
- 4th quarter 2007
- ≈ 800 swap bodies



VRP: Experiments

- Original data from project partner

- 4th quarter 2007
- ≈ 800 swap bodies
- ≈ 10 depots



VRP: Experiments

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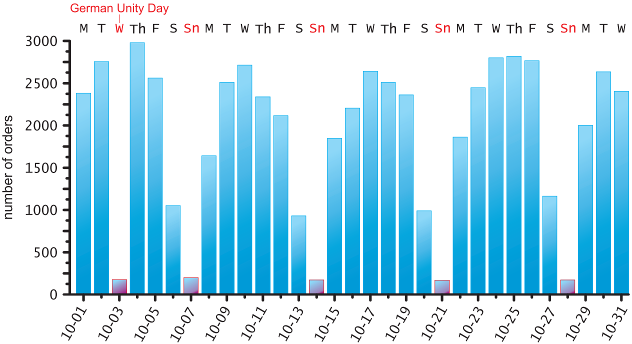
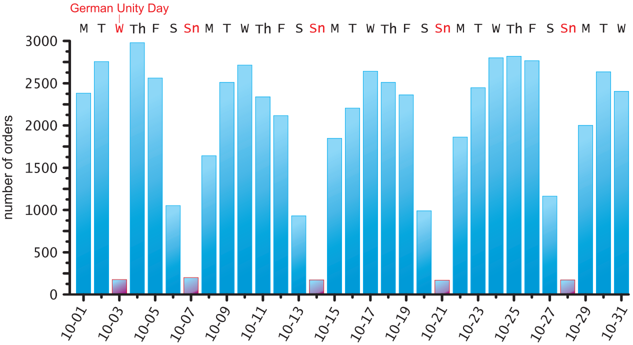
- ≈ 10 depots
- ≈ 800 pickup and delivery locations



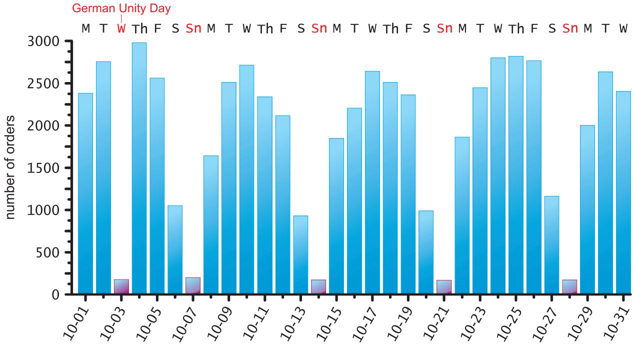
- Original data from project partner

- 4th quarter 2007
- ≈ 800 swap bodies
- ≈ 10 depots
- ≈ 800 pickup and delivery locations
- ≈ 160 – 3000 orders per day

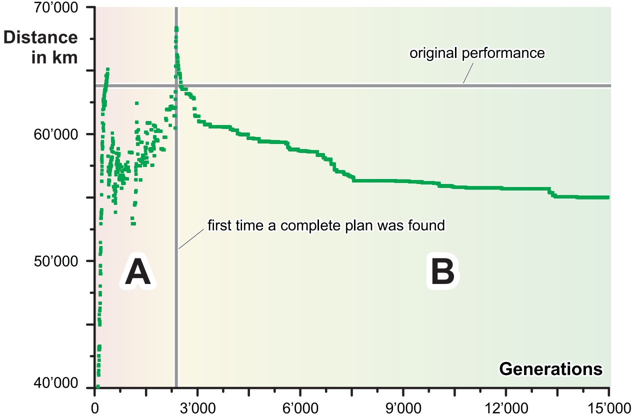


- Original data from project partner

- 4th quarter 2007
- ≈ 800 swap bodies
- ≈ 10 depots
- ≈ 800 pickup and delivery locations
- $\approx 160 - 3000$ orders per day
- $\approx 75\%$ fill rate, lean flow of goods



- Mon, 2007-12-24
- 642 orders
- original: 63 812km



- Mon, 2007-12-24
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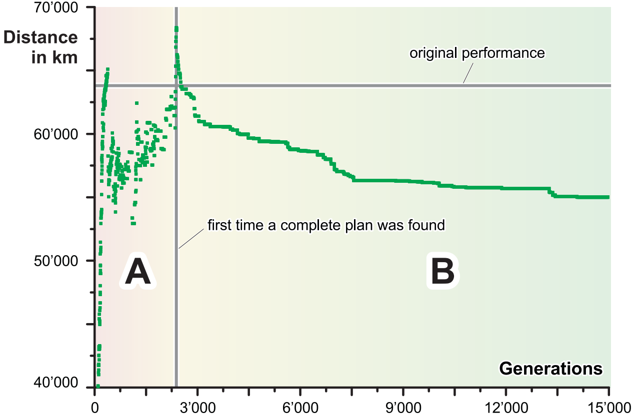
- **A**: assign all orders



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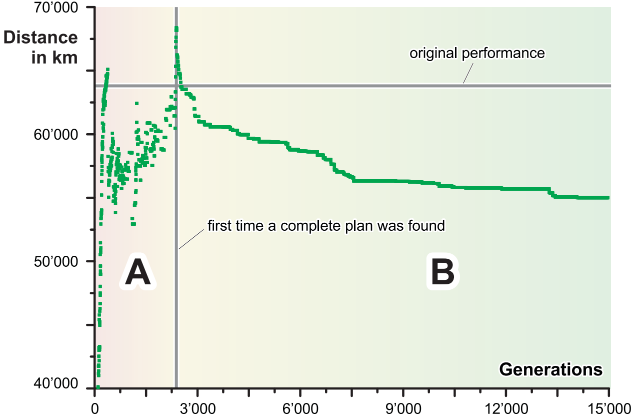
- **A**: assign all orders
- **B**: improve solutions



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- Mon, 2007-12-24
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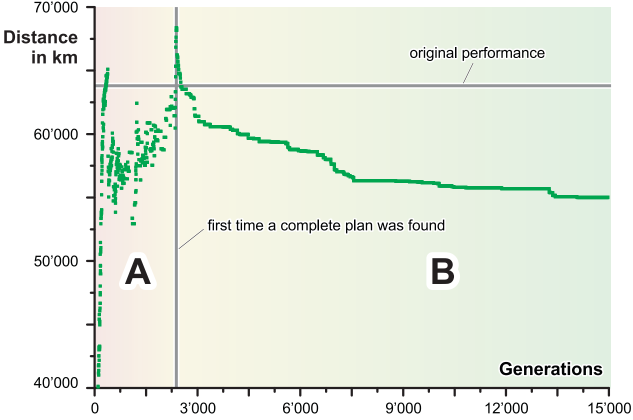
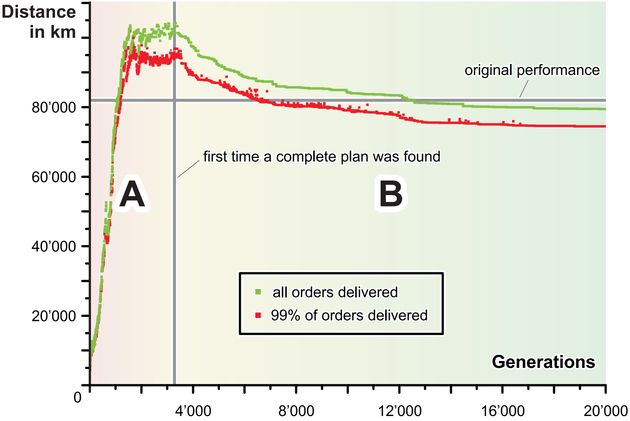
- **A**: assign all orders
- **B**: improve solutions
- 54 993km



- Sat, 2007-11-03
- 1016 orders
- original: 82 013km



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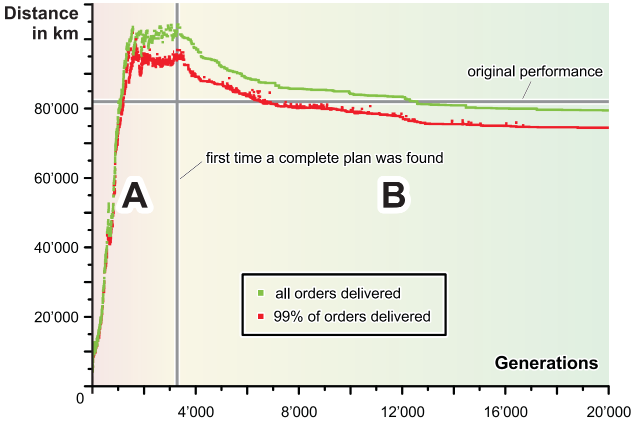

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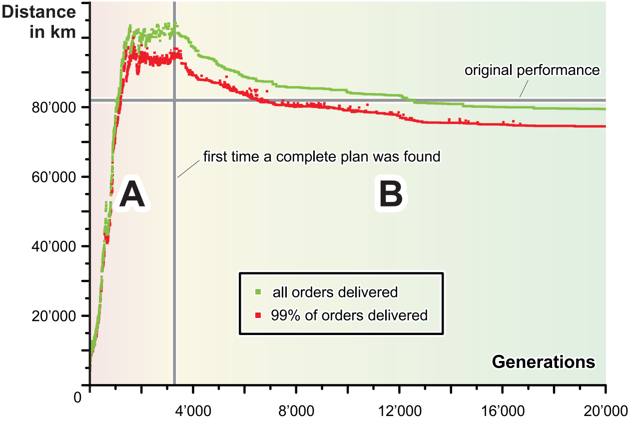

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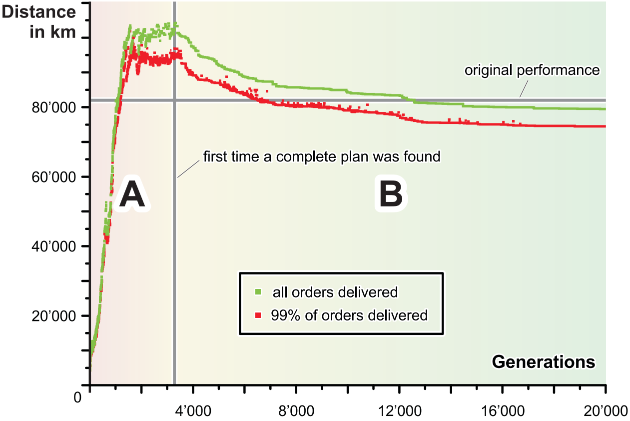

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谢谢
Thank you

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Caspar David Friedrich, "Der Wanderer über dem Nebelmeer", 1818
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