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Traffic simulations for innovative mobility concepts

XXXXI Heidelberg Physics Graduate Days

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Our plan for today

1	Welcome and warm-up	» Our life as a professional: CVs » Your opinion on future urban mobility: Mentimeter
2	Introduction to traffic modelling	» Traffic modelling approaches: 4 Step-Model vs. activity-based modelling » How to navigate: Introduction to navigation optimization » Approx. 15:30: BREAK and informal discussions » The mathematics behind: Deep-dive into various traffic models
3	Presentation of our Milan 2030 project and feedback	» The Milan setting: Our approach to simulate shared and self-driving cars » Simulation implementation: Data, pooling and integration » Results for Milan and outlook » Q&A and Feedback

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Part 1:
Welcome and Warm-Up

Disruptive trends are changing the way people are being transported

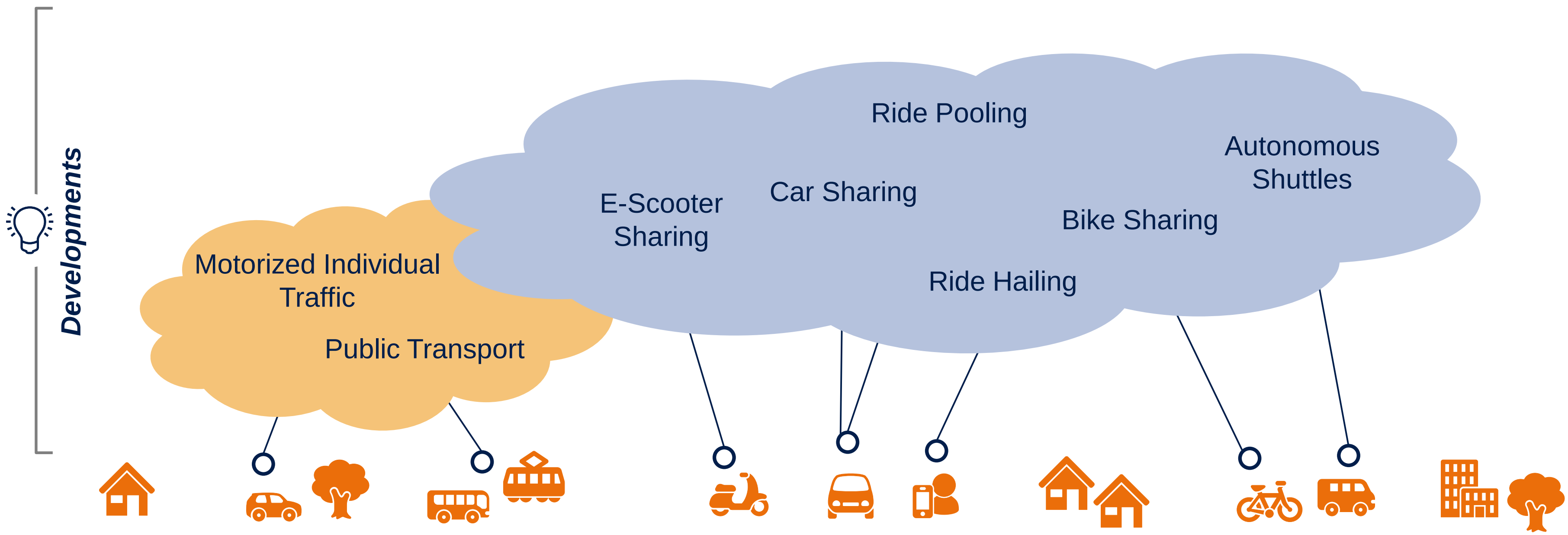
Trends

Urbanization
Populations and life expectancy are growing and producing megacities

Digitization
Enhanced services are based on lean applications, big data ecosystems, and data analytics

Shared Economy
Private ownership is giving way to flexibility and on-demand services

Sustainability
Awareness for infrastructure utilization, public areas, and emissions is increasing



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Part 2:
Introduction to traffic modelling

Introduction to traffic modelling

Transportation modelling supports decision making processes and allows for a scenario analysis of innovative mobility services

Travel models provide a systematic framework to analyze mobility behavior and the response to change. The type of travel model appropriate depends on the scope of the question at hand.

Model	Approach	Application
Sketch planning approach	» Easy to implement spreadsheet of GIS-based techniques to generate rough estimates of travel demand and produce order-of-magnitude information	» Appropriate for specific targeted analyses for small scale use cases
Trip-based approach	» Models are based on individual person trips, including the estimation of sinks and sources per geographic zone, the connection of these via trips, the travel mode choice and specific route assignment.	» Aggregated traffic forecast analysis e.g. for infrastructural planning
Activity-based approach	» Based on the assumption that people's activities result in their travel. The model considers the activity agenda derived from activity scheduling decisions on the level of individual people.	» Allow for dis-aggregated modelling and e.g. used to analyse emissions.

The goal of transport modelling is to generate origin-destination matrices that represent the mobility behavior of the population, and to adjust city and transport planning accordingly.

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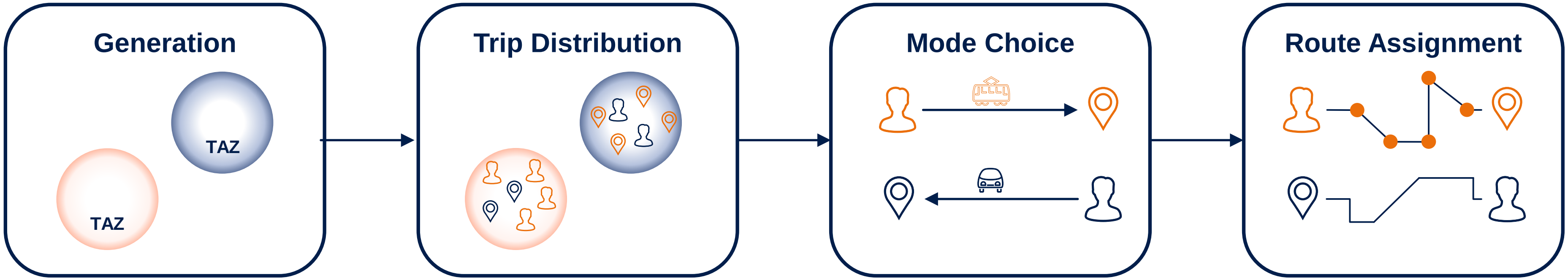
Traditionally the four-step travel model is used for transportation forecasts

The trip-based approach in the four-step model makes use of socioeconomic data to create travel routes.

Trip-based approach

Step	Description
Trip generation	» Determination of sources and sinks distributions for trips for traffic analysis zones, derived from e.g. household demographics and other socio-economic factors
Trip distribution	» Matching of sources to sinks as origin-destination relations, e.g. using a gravity model function
Travel mode choice	» Computation of the proportional distribution between origins and destinations for particular transportation modes
Route assignment	» Allocation of trips between origin and destination via a particular mode to a specific route. Route choice may depend travel time and congestion states



Mathematical constructs are used to generate and distribute trips and define routes from socioeconomic data.

See “Modelling Transport” by J. Ortúzar and L. Willumsen, Wiley 2011.

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Four step model – Trip generation

The trip-based approach in the four-step model makes use of socioeconomic data to create travel routes.

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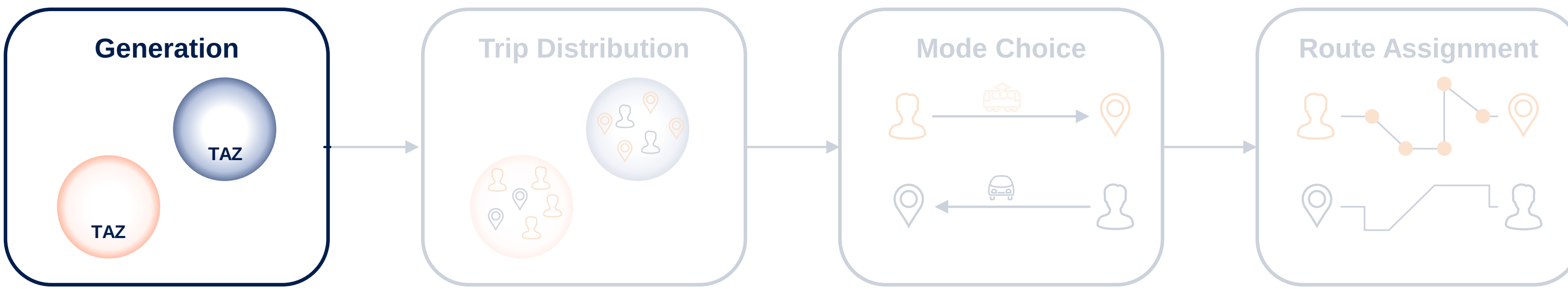
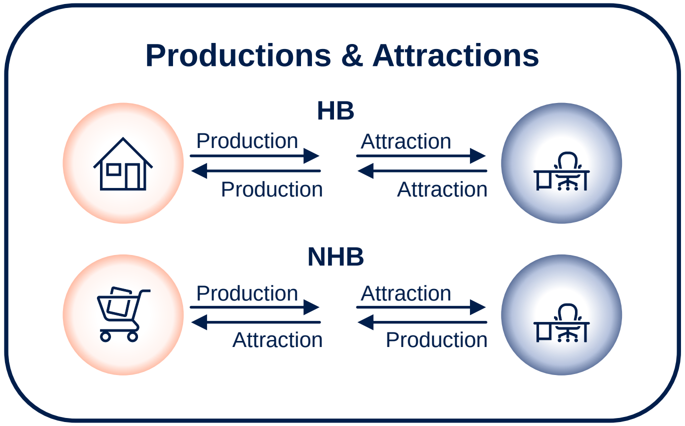


Basic definition for trip generation modelling

Terminology

- ***Trip / Journey:*** One-way movement from a point-of-origin to a point of destination
- ***Home-based trip (HB):*** Either the origin or destination of the trip is the home of the trip maker
- ***Non-home-based trip (NHB):*** Neither end of the trip is the home of the trip maker
- ***Trip production:*** The home end of an HB trip or origin of a non-HB trip
- ***Trip attraction:*** The non-home end of an HB trip or destination of a non-HB trip
- ***Trip generation:*** Total number of trips generated by households within a zone



Purpose Characterisation

- Differentiating between different trip purposes
  - *Mandatory*
    - Travel to work
    - Travel to school or college
  - *Optional*
    - Shopping
    - Recreational
    - Escort
    - Other

Time of Day Characterisation

- Differentiating between peak and off-peak trips

Person Type Characterisation

- Differentiating between socioeconomic attributes
  - Income level
  - Car ownership
  - Household size and structure

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Different modelling approaches allow to derive future trip generation vaules

Different approach allow to predict the total number of generated and attracted trips for each individual zone.

Model	Approach	Method Formulation
Growth-Factor Modelling	» Simple method where the future number of journey is derived from the current state with respect to a parameter (population, income, car ownership, etc.) dependent growth factor.	$T_i = F_i t_i$ $F_i = \frac{f\left(P_i^d, I_i^d, C_i^d\right)}{f\left(P_i^c, I_i^c, C_i^c\right)}$
Multiple Regression Analysis	» Find a linear dependency between the characteristic attributes for differentiated zones or even individual households. The latter removes the negligence of intra-zone variation, but is overall more expensive in terms of data collection, calibration and operation.	$Y_i = \theta_0 + \theta_1 X_{1i} + \theta_2 X_{2i} + \ldots + \theta_k X_{ki} + E_i$
Cross-Classification	» Assuming fairly stable trip generation rates the cross-classification approach predicts the number of trips as a function of the household attributes. The data foundation is based on empirical studies.	$t^p(h) = \text{average number of trips with purpose } p$ $a_i(h) = \text{number of households of type h in zone i}$ $O_i^{pq} = \sum_{h \in \mathrm{H}(q)}^{q} a_i(h) t^p(h)$

The trip generation is the foundation to derive the trip distribution from the origins and destinations.

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Four step model – Trip distribution

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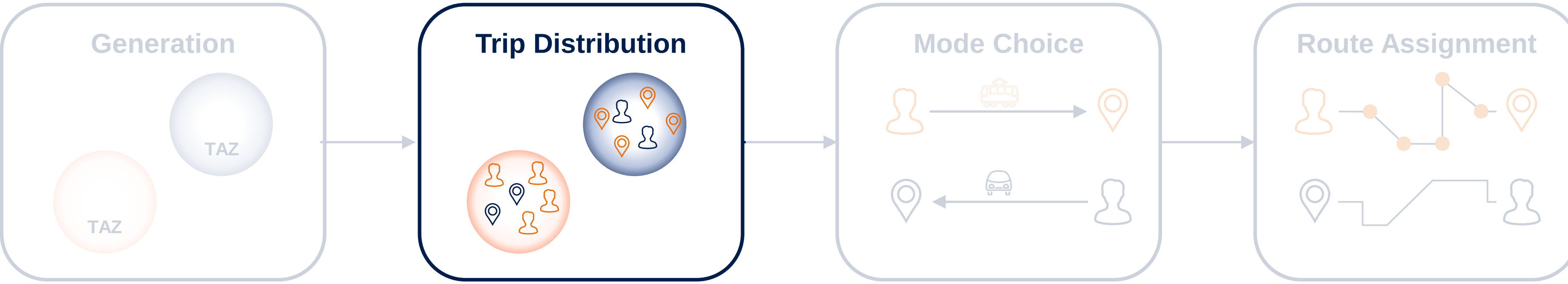

Trip distribution connects the origin and destination of modelled travellers

Trip distribution develops the productions and attractions derived during the trip generation step in order to establish a better understanding of trip patterns e.g. in the form of an OD-Matrix.

Trip matrix

» Two dimensional array where each of the rows and columns represents one of the traffic zones producing and attracting travel demand
- › The rows correspond to trip origins and are connected to corresponding destination zones given as columns
- › Diagonal entries represent intra-zonal trips
- › Trip matrices can be disaggregated e.g. by purpose, person type, time of day, …

- › T_{ij}^{kn} are trips from i to j by mode k and person type n
- › O_i^{kn} is the total number of trips originating in zone i
- › D_j^{kn} is the total number of trips ending in zone j

- › p_{ij}^{k} is the proportion of trips from i to j by mode k
- › c_{ij}^{k} is the generalized cost of travel between i to j by mode k which includes waiting time, interchange time, walking time, …

Origins \ Destinations	1	2	…	j	…	z	$\sum_j T_{ij}$
1	T_{11}	T_{12}		T_{1j}		T_{1z}	O_1
2	T_{21}	T_{22}		T_{2j}		T_{2z}	O_2
…							
i	T_{i1}	T_{i2}		T_{ij}		T_{iz}	O_i
…							
z	T_{z1}	T_{z2}		T_{zj}		T_{zz}	O_z
$\sum_i T_{ij}$	D_1	D_2		D_j		D_z	T

Constraints

» Depending on whether the O_i or D_j are known, the model can be origin or destination constrained (single) or double constrained if both are known
- › $\sum_j T_{ij} - O_i = 0$
- › $\sum_i T_{ij} - D_j = 0$

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Growth-Factor methods for a given OD-Matrix

Uniform Growth Factor

- If a general growth rate τ is known, the factor can be applied to a given base-year trip matrix t (see below) to generate an updated trip matrix T:

$$T_{ij} = \tau t_{ij}$$

- It is usually unrealistic to make such an assumption. Individual zones will develop differently from one another.

Origins	Destinations 1	2	3	4	$\sum_j$
1	5	50	100	200	355
2	50	5	100	300	455
3	50	100	5	100	255
4	100	200	250	20	570
$\sum_i$	205	355	455	620	1635

Sample base-year trip matrix

Singly Constrained Growth

- If the expected growth is only known for either the origins (see below) or the destinations, a zone specific growth factor τ_i can be determined from the ratio of target value to base-year total:

$$T_{ij} = \tau_i t_{ij} \; (origin\ specific)$$
$$T_{ij} = \tau_j t_{ij} \; (destination\ specific)$$

Origins	Destinations 1	2	3	4	$\sum_j$	Target O_i
1	5	50	100	200	355	400
2	50	5	100	300	455	460
3	50	100	5	100	255	400
4	100	200	250	20	570	702
$\sum_i$	205	355	455	620	1635	1962

Origin-constrained growth table

Doubly Constrained Growth

- Given both origin and destination growth rates, an iterative solving approach as introduced by Fratar or Furness can be applied:

$$T_{ij} = t_{ij}\tau_i\Gamma_j A_i B_j = t_{ij} a_i b_j$$

- Set $b_j = 1$ and solve for a_i, then keep a_i and solve for b_j, and repeat iteratively

Origins	Destinations 1	2	3	4	$\sum_j$	Target O_i
1	5,25	44,12	98,24	254,25	401,86	400
2	45,30	3,81	84,78	329,11	463	460
3	77,04	129,50	7,21	186,58	400,33	400
4	132,41	222,57	309,77	32,07	696,82	702
$\sum_i$	260	400	500	802	1962	
Target D_j	260	400	500	802		1962

Solution to the doubly constrained matrix expansion

Growth-factor models are highly dependent on the matrix accuracy, most reasonable for short-term planning, and do not include changes in transportation modes and costs.

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The gravity distribution model punishes distance and travel time and favors attractive origins and destinations

Simple Gravity Model	» Gravity distribution models makes use of the assumption that the interaction, i.e. trips, between two places decreases with increasing distance, time and cost, but increases with the attractiveness of these places. In analogy to the gravitation in physics, the simplest formulation, with P_i, P_j the population of two towns, d_{ij} the distance between them, and α a proportionality factor, has the following functional form: $$T_{ij} = \frac{\alpha P_i P_j}{d_{ij}^2}$$
Deterrence Function	» In a more sophisticated formulation, the number of trips O_i originating in one zone and ending in another (D_j) are included, as well as a more generic formulation of a deterrence function driven by the cost of travel c_{ij} between the two zones: $$T_{ij} = \alpha O_i D_j f(c_{ij})$$ $f(c_{ij}) = \exp(-\beta c_{ij})$ exponential function $f(c_{ij}) = c_{ij}^{-n}$ power function $f(c_{ij}) = c_{ij}^{n} \exp(-\beta c_{ij})$ combined function
Constrained Models	» Again considering the growth constraints within the model, the two balancing factors A_i, B_j can be introduced: $$T_{ij} = A_i B_j O_i D_j f(c_{ij})$$ $$A_i = \frac{1}{\sum_j B_j D_j f(c_{ij})} \text{ and } B_i = \frac{1}{\sum_i A_i O_i f(c_{ij})}$$

Synthetic models such as the gravity distribution model can also be motivated through a mathematical framework.

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The entropy-maximizing approach is a mathematical framework to derive synthetic distribution models

Using the entropy-maximizing approach the gravity distribution model will be derived

Assumption: All micro states consistent with a given macro state are equally likely to occur

Problem: Identify meso states which are most likely to occur given the constraints on the macro state

Entropy Maximization

- Considering combinatorics it can be stated that the number of micro states $W\{T_{ij}\}$ associated with meso state T_{ij} is

$$W\{T_{ij}\} = \frac{T!}{\Pi_{ij} T_{ij}!}$$

- Maximizing $W\{T_{ij}\}$ can be reformulated using the log-function and Sterling's short approximation:

$$\log W = \log T! - \sum_{ij} \log T_{ij}!$$

$$\log W = \log T! - \sum_{ij} (T_{ij} \log T_{ij} - T_{ij})$$

$$\log W' = - \sum_{ij} (T_{ij} \log T_{ij} - T_{ij})$$

- Maximizing $\log W'$ (also known as entropy function) enables the generation of models to estimate the most likely meso states (e.g. matrix T).

The key to this method is the identification of suitable micro, meso and macro state descriptions together with the macro level constraints that must be met.

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The entropy-maximizing approach is a mathematical framework to derive synthetic distribution models

Gravity distribution model

- Considering the constraints for trip production and attraction as well as an additional constraint on the overall cost,

$$O_i - \sum_j T_{ij} = 0$$

$$D_j - \sum_i T_{ij} = 0$$

$$C - \sum_{ij} T_{ij} c_{ij} = 0$$

- the constrained maximisation problem can be handled through a Lagrangian formulation:

$$L = \log W' + \sum_i \alpha_i' \{O_i - \sum_j T_{ij}\} + \sum_i \alpha_i'' \{D_j - \sum_i T_{ij}\} + \beta\{C - \sum_{ij} T_{ij} c_{ij}\}$$

$$\frac{\partial L}{\partial T_{ij}} = -\log T_{ij} - \alpha_i' - \alpha_j'' - \beta c_{ij} = 0$$

$$T_{ij} = \exp(\alpha_i') \exp\left(\alpha_j''\right) \exp(-\beta c_{ij}) = A_i O_i B_j D_j \exp(-\beta c_{ij})$$

Framework

- The entropy maximization approach is flexible as different constraints can be included in the framework
  - The objective function is convex and that given the used constraints, the optimization problem has a unique solution
  - The theoretical framework applied provides a physical analogy for improved interpretation
  - The appropriateness of the model depends on the acceptability of the assumptions

The gravity distribution model can be used to expand a given trip matrix, assuming certain cost values for the inter-zonal trips.

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Relating the gravity distribution model to the expanding trip expectations

Cost matrix

» The following cost matrix c_{ij} is assumend to be given, also $\beta = 0.1$

Origins	Destinations 1	2	3	4	Target O_i
1	3	11	18	22	400
2	12	3	12	19	460
3	15,5	13	5	7	400
4	24	18	8	5	702
Target D_j	260	400	500	802	1962

» The individual cost values are converted via the deterrence function $\exp(-\beta c_{ij})$

Origins	Destinations 1	2	3	4	$\sum_j$
1	0,74	0,33	0,17	0,11	1,35
2	0,30	0,74	0,30	0,15	1,49
3	0,21	0,27	0,61	0,50	1,59
4	0,09	0,17	0,45	0,61	1,31
$\sum_i$	1,34	1,51	1,52	1,36	5,74

Base trip matrix

» Expanding the cell values by the ratio of total trips over total cost a base trip matrix is derived

Origins	Destinations 1	2	3	4	$\sum_j$	Target	Ratio
1	253,12	113,73	56,48	37,86	461,19	400	0,87
2	102,91	253,12	102,91	51,10	510,04	460	0,90
3	72,52	93,12	207,23	169,67	542,54	400	0,74
4	31,00	56,48	153,52	207,23	448,23	702	1,57
$\sum_i$	459,5423	516,445	520,1463	465,8664	1962		
Target	260	400	500	802		1962	
Ratio	0,57	0,77	0,96	1,72			

Gravity model matrix

» Applying the Furness iterations to the balancing factors a_i and b_i the matrix elements of the gravitational expansion are derived:

Origins	Destinations 1	2	3	4	$\sum_j$	Target	Ratio	a_i
1	157,04	100,36	66,14	76,46	400,00	400	0,87	1,25
2	57,48	201,09	108,50	92,92	460,00	460	0,90	1,12
3	25,26	46,13	136,24	192,37	400,00	400	0,74	0,70
4	20,23	52,42	189,11	440,24	702,00	702	1,57	1,31
$\sum_i$	260,00	400,00	500,00	802,00	1962			
Target	260	400	500	802		1962		
Ratio	0,57	0,77	0,96	1,72				
b_j	0,50	0,71	0,94	1,62				

Using a given cost matrix and the previously derived origin and destination target values the expected OD-matrix can be derived.

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A gravity distribution model needs to be calibrated before use

The aim of the calibration is to reproduce the base-year trip pattern as close as possible.

Calibration Technique

The classical gravity model has $2Z + 1$ parameters (with Z the number of zones) – namely, A_i, B_j, and β.

- The A_i, B_j are already estimated as part of the Furness balancing factor operations
- The parameter β must be calibrated to make sure, that the trip length distribution is reproduced as closely as possible

A number of calibration techniques have been proposed, a popular method was developed by Hyman:

- Start with the following requirement for β:

$$c(\beta) = \sum_{ij} \frac{T_{ij}(\beta) c_{ij}}{T(\beta)} = c^* = \sum_{ij} (N_{ij} C_{ij}) / \sum_{ij} N_{ij}$$

where c^* is the mean cost for the OTLD and N_{ij} the observed number of trips

Iteration

1. Start the first iteration ($m = 0$) with an initial estimate $\beta_0 = \frac{1}{c^*}$
2. Calculate a trip matrix using the standard gravity model and β_0. Obtain the mean modelled trip cost c_0 and estimate $\beta_m = \frac{\beta_0 c_0}{c^*}$
3. Recalculate the trip matrix and obtain a new mean modelled cost. If it is sufficiently close to c^* stop, otherwise go on.
4. Re-estimate β as: $\beta_{m+1} = \frac{(c^* - c_{m-1})\beta_m - (c^* - c_m)\beta_{m-1}}{c_m - c_{m-1}}$
5. Repeat steps 3 and 4 as necessary

The gravitational distribution model is the most common model applied.

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Other synthetic models are less used, but offer real alternatives to the classic gravitational model

Generalizations of the Gravity Model	» The classical gravity model is by far the most established trip distribution model. Extensions of the model have been introduced in which other forms of deterrence functions are considered, e.g: $$T_{ij} = A_i O_i B_j D_j \exp(-\beta C_{ij} - \lambda T_{ij} C_{ij})$$
Intervening Opportunities Model	» The idea behind intervening opportunities models is that trip making is not explicitly related to distance but to the relative accessibility of opportunities for satisfying the objective of the trip. $$T_{ij}^m = \frac{O_i[\exp(-\alpha x_{m-1}) \exp(-\alpha x_m)]}{[1 - \exp(-\alpha x_m)]}$$ » The model uses distance as an ordinal variable instead of a continuous cardinal one as in the gravity model. It explicitly considers the opportunities available to satisfy a trip purpose at increased distance. » Still, the model is less used, probably due to the increased complexity at marginal gain, as well as the lack of suitable software
Disaggregate Approaches	» Disaggregate approaches move away from simple zonal based productions and attraction. Instead they increase disaggregation by e.g. focusing on journey purposes and person types. » These models do not deal with the number of trips to a particular destination but rather with the probability that a (representative) individual would choose a particular destination to satisfy some basic needs.

Having a modelled trip distribution, the next step is to include the modal split and model the choice of transport mode.

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Four step model – Travel mode choice

The trip-based approach in the four-step model makes use of socioeconomic data to create travel routes.

Trip-based approach

Trip generation	» Determination of sources and sinks distributions for trips for traffic analysis zones, derived from e.g. household demographics and other socio-economic factors
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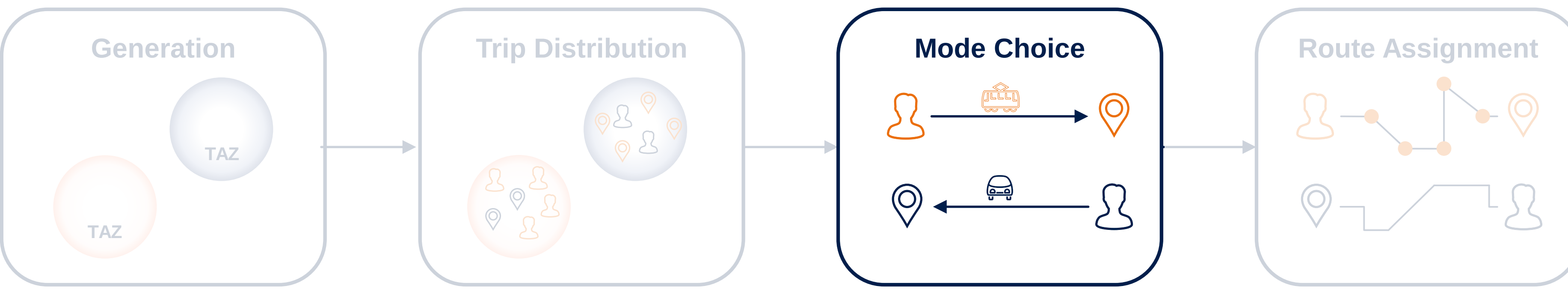

Mathematical constructs are used to generate and distribute trips and define routes from socioeconomic data.

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Modal split models

The modelling of modal splits is the most important element in transport planning and policy making.

Characteristics of traveller

- Generally assumed impact factors:
  - Car availability / ownership
  - Possession of drivers licence
  - Household structure
  - Income
  - Decisions made elsewhere
  - Residential density

Characteristics of trip

- Choice of mode is strongly influenced by:
  - Trip purpose
  - Time of day
  - Alone or with others

Characteristics of transport

- Quantitative factors:
  - Components of travel-time
  - Components of monetary costs
  - Availability and cost of parking
  - Reliability of travel time
  - Regularity of service
- Qualitative factors:
  - Comfort and convenience
  - Safety, protection and security
  - Demands of the driving task
  - Opportunities to undertake other activities during travel

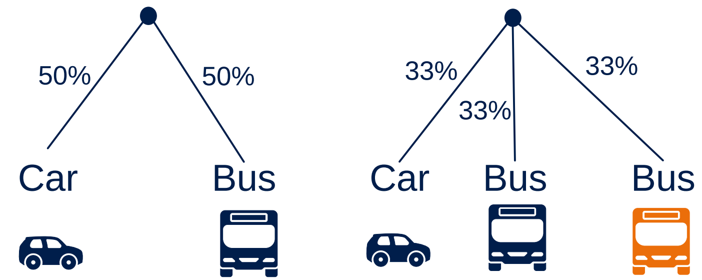
The modal split can be modelled using logit functions for discrete choices

Logit

$$P_i = \frac{e^{V_i}}{\sum_m e^{V_m}}$$

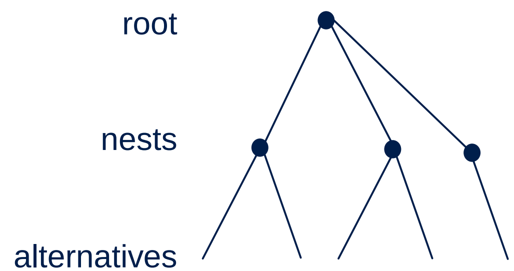
V_i ≔ utility function, usually defined as a linear combination of variables such as *access time*, *in-vehicle travel time*, *cost/income*, …

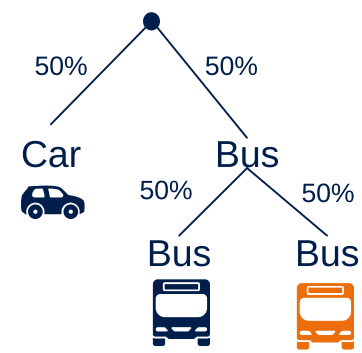
Red-bus / blue-bus problem:



Nested Logit

- The structure is characterized by grouping all subsets of correlated (similar) options into hierarchies / nests.
- The introduction of information from lower nests in the next higher nest is done by means of the utilities of the underlying alternatives.
- The probability that a given mode of transport is selected, can be computed as the product of the marginal probabilities.





The most applied model today seems to be the mixed logit model which includes random taste variations, unrestricted substitution patterns, and correlation in unobserved factors over time.

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Four step model – Route assignment

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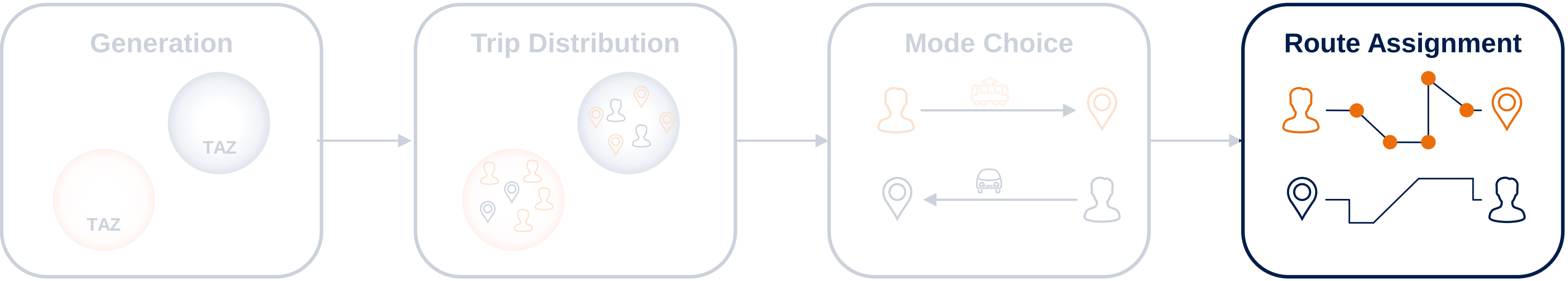

Mathematical constructs are used to generate and distribute trips and define routes from socioeconomic data.

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The Dijkstra Algorithm is well established to find shortest paths between nodes in a graph

Scope

- » In general the algorithms finds the shortest path between a source node and every other node in the system
- » It can be used for routing when starting at an origin node and finding the shortest path to a destination node
  - › Nodes can be interpreted as cities or addresses and costs according to distance or driving time assigned to edges
  - › Notably also used for Intermediate System to Intermediate System and Open Shortest Path First

Dijkstra Algorithm

1. Initialize all nodes as unvisited and set a tentative distance value (e.g. infinity for all but starting node which is 0)
2. Consider distance to all unvisited neighbors of current node, calculate tentative distance, set if smaller than existing value, and mark current node as visited
3. Repeat step two until the destination node has been marked visited (in practice, the algorithm can be stopped as soon as the destination node has the smallest tentative distance among all unvisited nodes)

```
function Dijkstra(Graph, source):
    create vertex set Q
    for each vertex v in Graph:
        dist[v] <- INFINITY                     //Unknown distance from source to v
        prev[v] <- UNDEFINED                    //Previous node in optimal path from source
        add v to Q                              //All nodes initially in Q (unvisited nodes)

    dist[source} <- 0                           // Distance from source to source

    While Q is not empty:
        u <- vertex in Q with min dist[u]       //Node with least distance will be selected first

        remove u from Q

        from each neighbour v of u:             //where v is still in Q
            alt <- dist[u] + length(u,v)
            if alt < dist[v]:                   //a shorter path to v has been found
                dist[v] <- alt
                prev[v] <- u

    return dist[], prev[]
```

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Planning my trip to Heidelberg with Djikstra

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Different routes are possible considering travelling by car or train

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Iteration 1: Drive by car via Bonn

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Iteration 2: Take the train from Köln to Frankfurt Flughafen

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Iteration 3: Drive by car from Köln to Limburg

Iteration 4: Take the train to Mannheim via Frankfurt Flughafen

Iteration 5: Drive from Köln via Bonn to Koblenz

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Final Iteration: From Köln to Darmstadt via Limburg, and from Köln to Heidelberg via Bonn und Koblenz exceeds the current total time.

Taking the ICE Sprinter from Köln to Mannheim and then switching to the S-Bahn is the fastest way to reach Heidelberg

Transportation modelling supports decision making processes and allows for a scenario analysis of innovative mobility services

Travel models provide a systematic framework to analyse mobility behavior and the response to change. The type of travel model appropriate depends on the scope of the question at hand.

Model	Approach	Application
Sketch planning approach	» Easy to implement spreadsheet of GIS-based techniques to generate rough estimates of travel demand and produce order-of-magnitude information	» Appropriate for specific targeted analyses for small scale use cases
Trip-based approach	» Models are based on individual person trips, including the estimation of sinks and sources per geographic zone, the connection of these via trips, the travel mode choice and specific route assignment.	» Aggregated traffic forecast analysis e.g. for infrastructural planning
Activity-based approach	» Based on the assumption that people's activities result in their travel. The model considers the activity agenda derived from activity scheduling decisions on the level of individual people.	» Allow for dis-aggregated modelling and e.g. used to analyse emissions.

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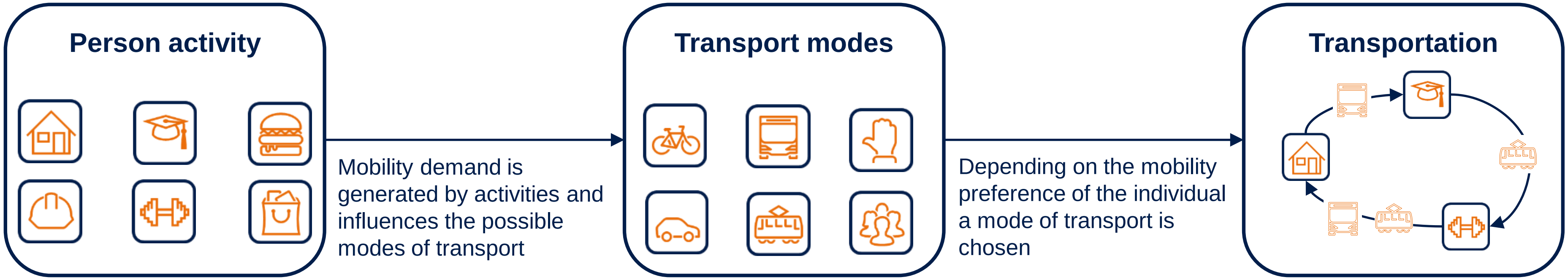
Understanding activities and user stories as drivers of mobility demand

The activity-based approach considers travel behavior of people as driven by their activities.

Activity-based models

» The idea of activity-based models
- › The fundamental premise is that travel demand can be derived from people's needs and desires for activities
- › The models are based on behavioral theories about how people make decisions given certain constraints
- › Activity-based models integrate explicit spatial-time constraints and establish a link between actual activities and travel
- › Constraints and linkages allow for a more realistic representation of the effect of travel conditions on activities and travel choice



The mobility sector can be seen as a system in which internal and external factors impact the activities and the mobility behavior of the people.

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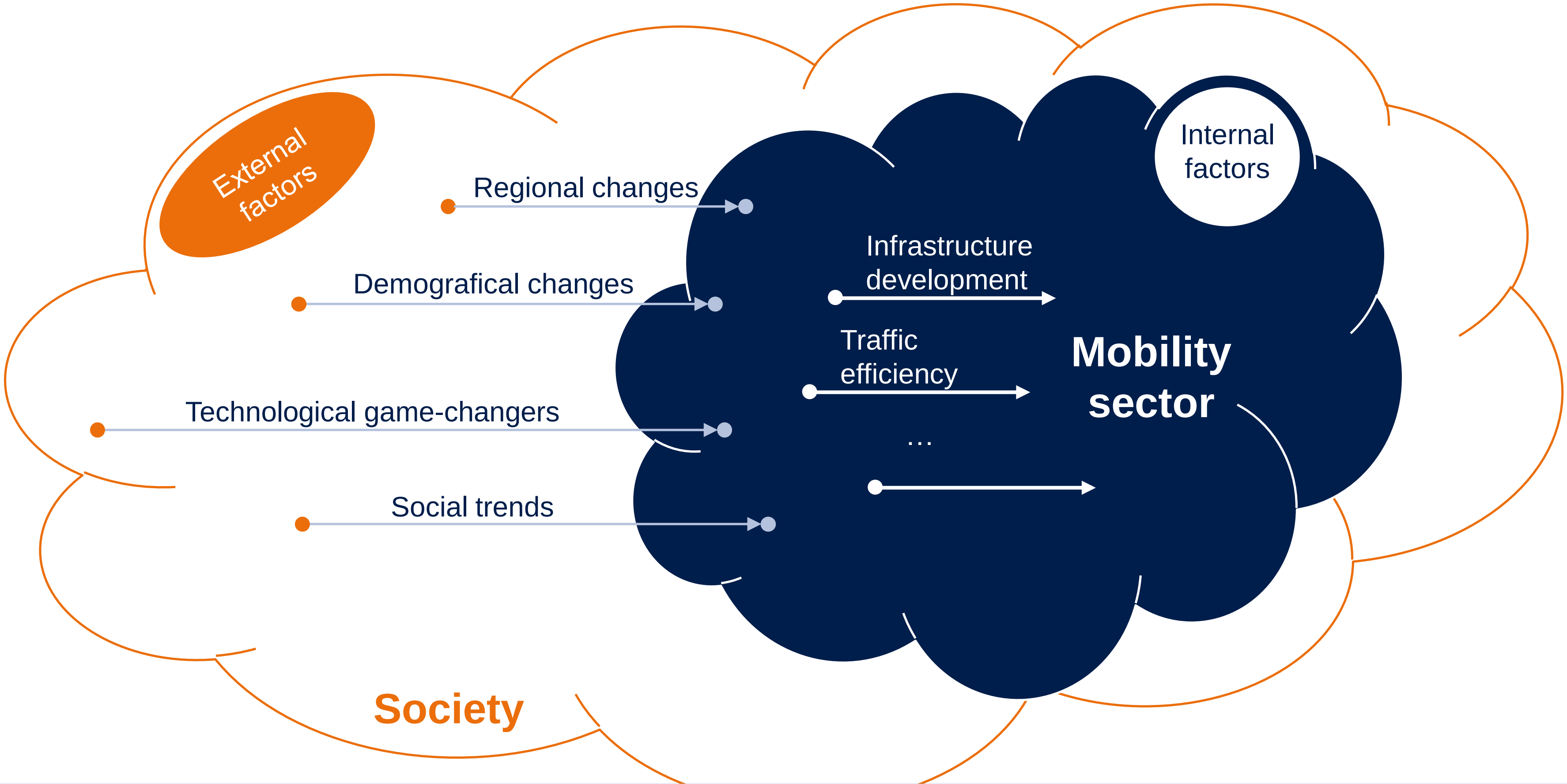
In system theory, one aims to identify external and internal factors that drive the outer and inner system

In our case the outer system can be seen as the society and the inner system is the mobility sector.



From the mobility sectors point of view, we cannot change the external factor, but we have to optimise the internal factors in order to manager mobility demand.

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Activity-based modelling enables us to understand the mobility demand

In trip-based modelling one focusses on single trips from A to B and their mode of transport. With activity-based modelling one knows the dependencies of single trips and their reasons.

Understanding mobility demand

- Social trends
- Technological game-changers

Activity

Demand of doing something in order to get satisfied, e.g. work, stay at home, holiday traveling, family meetings

» Activity-based tours

- Demografical / regional changes
- Infrastructure development

Mobility

Demand of moving from A to B – always sourced by one activity

» Mobility-related trips

- Current traffic

Traffic

Demand on travelling at a specific route in order to come from A to B

» Traffic-related routes

The driving factor of activity demand can change much fast than the driving factors of the mobility demand. Therefore activity-based modelling becomes important for city planners and policy makers.

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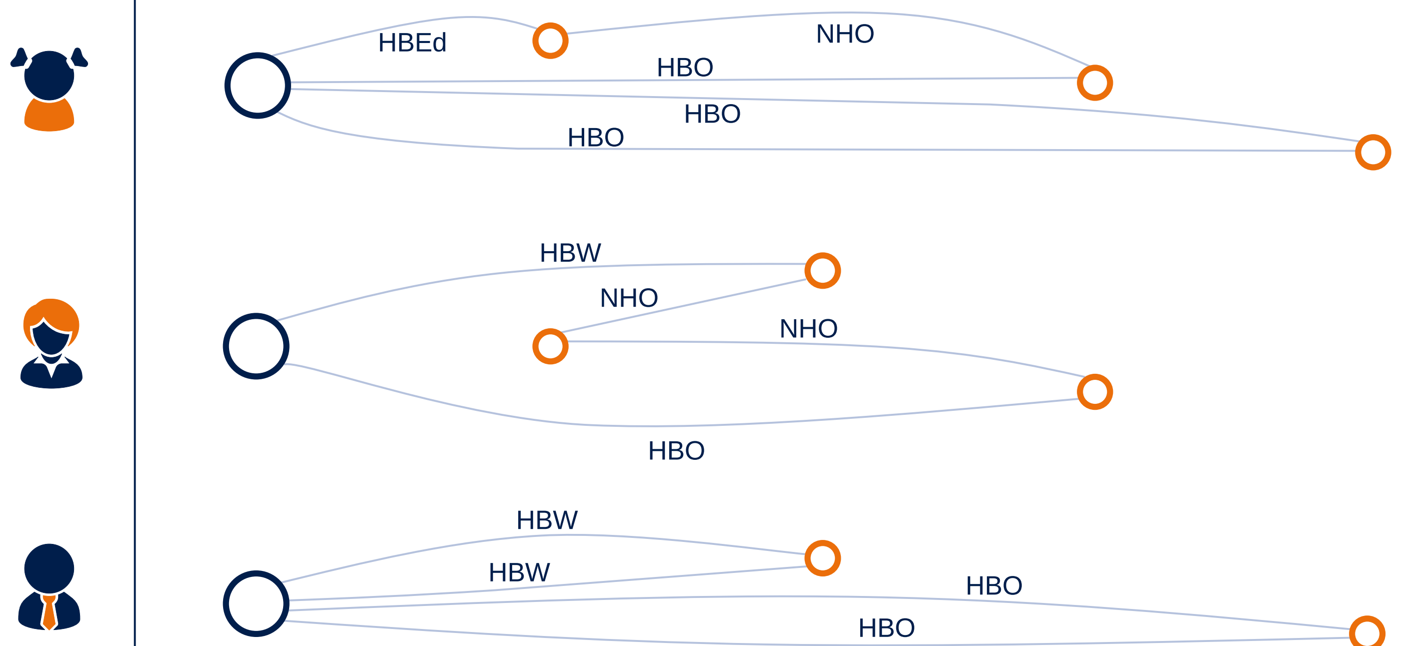
The “tour” concept in activity-based modelling combine single trips to tours

Activities are often directly related to their places. Therefore the mobility between these places can be directly related to activities.

Place	**HOME**	**SCHOOL**	**OFFICE**	**STORE**	**SPORT CLUB**
Activity	*Being at home*	*Studying*	*Working*	*Shopping*	*Training*



Both the shopping and sports activity are household dependent, and influence the trips and mode of transport.

A good classical model can pick up the individual trips despite the complexity, but not their interrelationships.

Again, the interdependency with other people influences the trips, here especially the starting point

Tours are classified by their length in time and their most relevant activity.

Advantages of activity-based modelling compared with trips and tours

Activity-based modelling

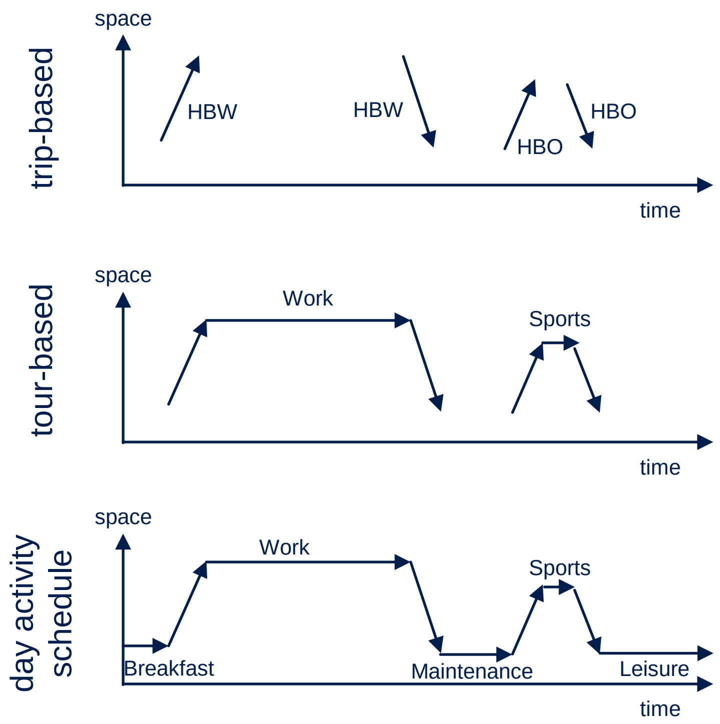
Advantages:

- Allows for an impact evaluation of i.e. policy, mobility service, or infrastructural changes
- Provide robust capabilities and sensitivities to evaluate i.e. pricing scenarios
- Activity based models allow for a broad set of performance metrics on a disaggregate person-level

Disadvantages:

- External trips from outside the study area needs to be added
- Special trip generators (airports, shopping malls are not considered)
- Commercial vehicles are not part of the model
- Additional “noise trips” (e.g. Police, Emergency services, etc.) are missing as well.

Approach comparison



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Activity-based models incorporate the highest level of person and household detail and are becoming more relevant to model MaaS

Model Type	Spatial / Temporal Detail	Person / Household Detail	Policy Sensitivity	Run Time	Cost
Sketch planning approach	Low	Low	Low	Low	Low
Trip-based approach	Low - Moderate	Moderate	Moderate	Moderate	Moderate
Activity-based approach	Moderate - High	High	Moderate - High	Moderate	Moderate

After modeling and routing the mobility demand, traffic simulation models are necessary to run traffic simulations and to allow forecasting and planning.

Introduction into traffic simulation models

Differentiating between different model classes (1/2)

Resolution

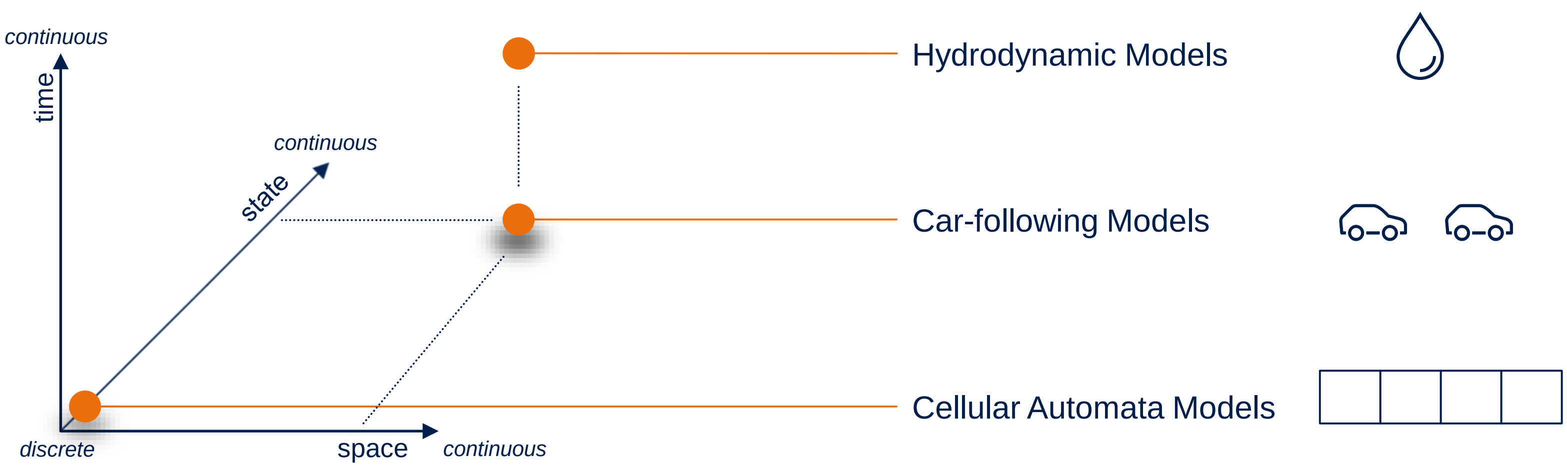
Microscopic: States of individual particles, i.e. travelers and vehicles. Simulations focus on individual behavior, dynamics and interactions.

Mesoscopic: Mix of microscopic and macroscopic description, e.g. describing changes in macroscopic variables through in- / outflow of microscopic particles.

Macroscopic: Models aggregated particles in analogy to fluids or gas, and focuses on general effects such as the velocity of jam fronts.

Variables

Discrete vs. continous: Spatial, temporal, and state variables can be either discrete or continuous. In principle, all combinations are possible within traffic simulation models.



See Stochastic Transport in Complex Systems: From Molecules to Vehicles, Andreas Schadschneider, Debashish Chowdhury, Katsuhiro Nishinari. Elsevier – 2011.

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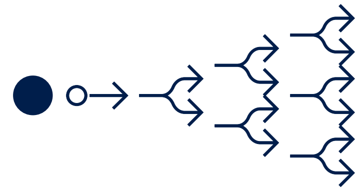
Differentiating between different model classes (2/2)

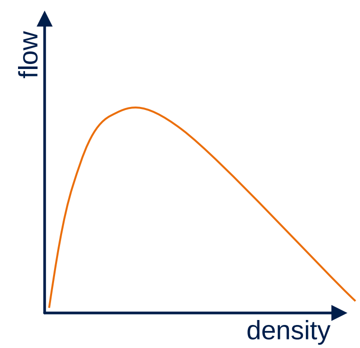
Dynamic

Deterministic vs. stochastic: Models with stochasticity include randomizations that impact the behavior and outcome.



Level of Detail

High vs. low fidelity: The degree of fidelity identifies the focus of the model, e.g. high fidelity models can depict realistic driving behavior while low fidelity models reproduce fundamental indicators.



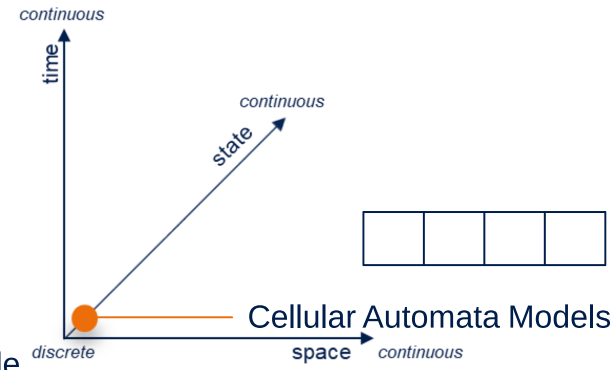
Cellular automaton

Nagel Schreckenberg model

Cellular Automata – Nagel Schreckenberg Model

Cellular Automata Models:

- Microscopic models depicting individual vehicles
- Discrete in space, time, and state variables (e.g. velocity)
- Both deterministic and stochastic, depending on the applied rules
- Low fidelity models that try to efficiently reproduce fundamental indicators



Nagel Schreckenberg Model:

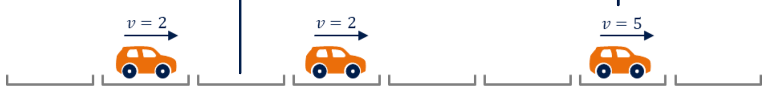
- Prototype of all cellular automata models
- Idea: Street as one-dimensional string of cells, where each cell can hold one vehicle
- Includes randomness that allows realistic behavior to emerge

Discrete cell:

- Length = 7.5m
- Corresponds to the average length of a vehicle plus the average distance to the next vehicle in a jam situation

Vehicle n :

- The variable v holds the current velocity (in cells) of the vehicle
- The velocity takes on integer values from 0 to v_{max}



The Nagel Schreckenberg model is easy to implement and the simplest form of cellular automaton model that reproduces realistic results, even including spontaneous jam formation.

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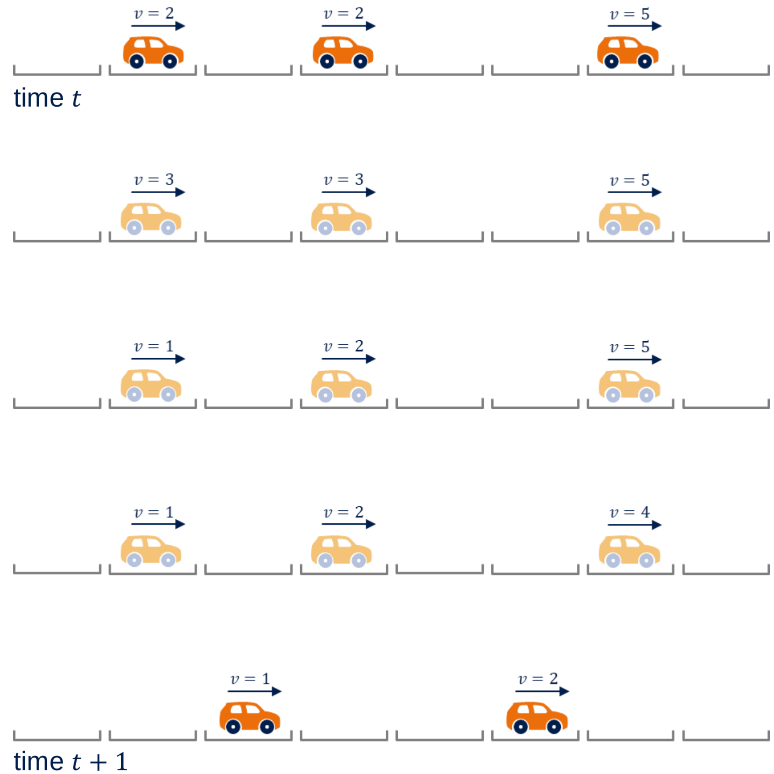
The steps of the Nagel Schreckenberg model

The Nagel Schreckenberg model makes use of four simple steps to define the transition between the state at time t and $t + 1$.

Prerequisites / Setup:

» Define the length of the automat (number of cells)
» Define the vehicle density, and distribute the vehicles randomly onto the automat
» Define the randomization probability p

1	Acceleration	» Cars accelerate by 1 unit, unless they have reached the maximal velocity v_{max} $$v \rightarrow \min(v_{max}, v + 1)$$
2	Safety Distance	» If necessary, cars decelerate in order to reduce the velocity to the number of open cells d ahead $$v \rightarrow \min(d, v)$$
3	Randomization	» The randomization factor introduces uncertainty into the model. Each car reduces the velocity v by 1 unit with probability p $$v \rightarrow v - 1 \text{ with probability } p$$
4	Driving	» The vehicles move according to the calculated velocity and the iteration repeats.



Hydrodynamic models

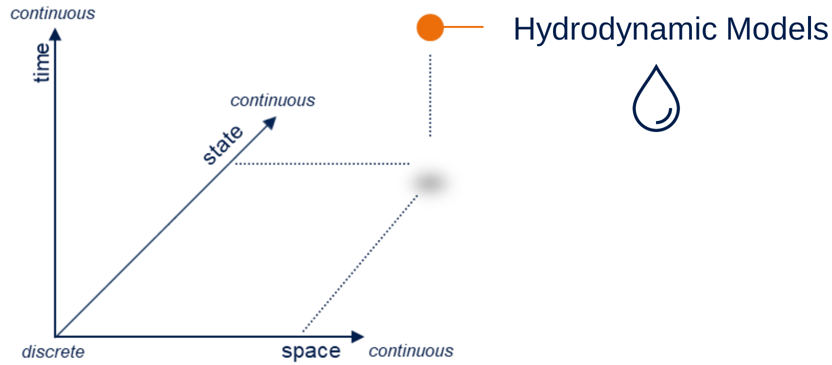
Simulating shockwaves

Hydrodynamic models

Hydrodynamic models make use of the continuity equation to describe density, flow, and velocity, and to derive traffic dynamics.

Hydrodynamic Models:

- Macroscopic models
- Continuous in space, time, and state variables (e.g. velocity)
- Usually deterministic models
- Low fidelity models that try to efficiently reproduce fundamental indicators



Lighthill-Whitham Theory (1955):

Starting point is the continuity equation: $\frac{\partial \rho(x,t)}{\partial t} + \frac{\partial J(x,t)}{\partial x} = 0$, with density $\rho(x,t)$ and flux $J(x,t)$

- The equation has the same structure as e.g. the continuity equation in hydro- or electrodynamics, and in general describes the transport of some quantity (here vehicles)
- It connects the temporal change in density $\frac{\partial \rho(x,t)}{\partial t}$, to the divergence of flux $\frac{\partial J(x,t)}{\partial x}$
- Within a closed system, the equation resembles the conservation of vehicles.

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Lighthill-Whitham theory continued

» Lighthill and Whitham made the assumption, that a direct static relation exists between the traffic flow $J(x,t)$ and the density $\rho(x,t)$, so that:

$$J(x,t) = J\big(\rho(x,t)\big) \text{ and } \frac{\partial\rho}{\partial t} + \frac{dJ(\rho)}{d\rho}\frac{\partial\rho}{\partial x} = 0$$

» LWR equation is a non-linear wave equation describing the propagation of kinematic waves, with the general formulation:

$$\frac{\partial\rho(x,t)}{\partial t} + v_e(\rho)\frac{\partial\rho(x,t)}{\partial x} = 0 \text{ with } v_e(\rho) = \frac{dJ}{d\rho} = v + \rho\frac{dv}{d\rho}$$

$v_e(\rho)$:= propagation velocity of density waves

v := vehicle velocity

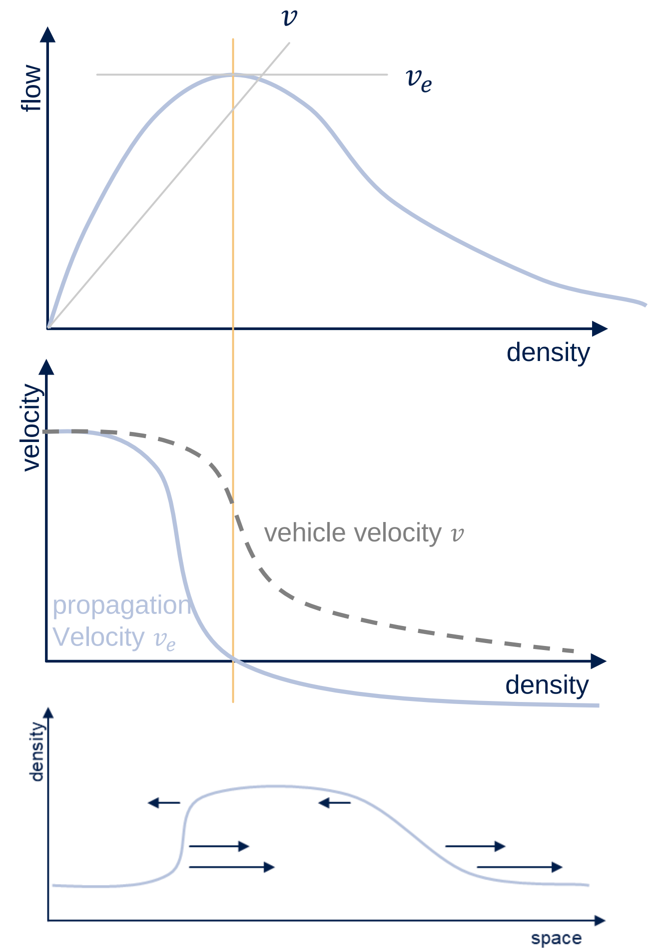
» In the LWR model, the fundamental diagram cannot be derived, but must be assumed. A simple choice is the Greenshields-Form:

$$J_G(\rho) = v_{max}\rho(1 - \frac{\rho}{\rho_{max}})$$

» At low densities the flux is linear to ρ with slope v_{max}, and at ρ_{max} it vanishes.

v_{max} := velocity in free flow phase

ρ_{max} := density in jammed state



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Car-following models

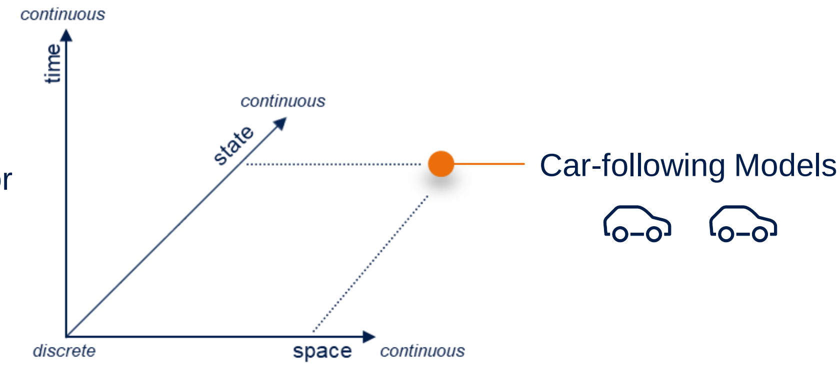
Krauß model as the foundation for current simulation software

Car-following models

Car-following models are microscopic models that consider vehicles as interacting, classical particles.

Car-Following Models:

- Microscopic models
- Continuous in space and state variables, and discrete in time
- Can include a parameter for a stochastic driver model
- High fidelity models that try to efficiently reproduce driver behavior



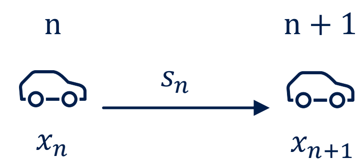
In general, the equation of motion for each vehicle is formulated as:

$\ddot{x}_n(t) = \frac{1}{\tau}[\dot{x}_{n+1}(t) - \dot{x}_n(t)]$, with τ as the reaction time of the driver

Krauß-Modell:

- Vehicles are described through a maximum velocity v_{max}, and additionally braking and acceleration potentials $b(v)$ and $a(v)$

$$-b \leq \frac{dv}{dt} \leq a$$



- Preventing accidents results in: $v_n(t + \Delta t) \leq \min[v_{max}, v_n(t) + a\Delta t, v_{safe}]$
- The braking potential $b(v)$ implies: $v_n(t + \Delta t) \geq v_n(t) - b\Delta t$
- Then, considering the distance s_n between the two vehicles, accidents will be avoided with:

$$v_n(t + \Delta t) \leq v_{n+1}(t) + \frac{s_n - v_{n+1}(t)\tau}{\tau_w(t)}, \text{ with } \tau_w = \tau_b + \tau, \; \tau_b = \frac{\bar{v}}{b}, \text{ and } \bar{v} = \frac{1}{2}(v_n + v_{n+1})$$

Wishful relaxation time (τ_w) | Reaction time of the driver (τ) | Average breaking time (τ_b)

Traffic simulation software

Three main simulation software players are visible in the European market

SUMO

- Developed and maintained by DLR
- Open source microscopic simulation software build on car-following models such as Krauss or Wiedmann.
- Focus on vehicle simulations, but sophisticated intermodality is being implemented step-by-step
- Integrated APIs for customizations

PTV

- German company founded in 1979; 700 employees worldwide
- Acquired by Porsche SE in 2017
- Software for macroscopic (PTV Visum) and multimodal microscopic (PTV Vissim) traffic simulations
- Microscopic simulation based on Wiedmann’s car-following model that focuses on the velocity difference between the leader and the follower
- Modular components for forecasting based on real-time traffic data (PTV Optima), route optimization (PTV Route Optimiser), and dispatching / matching (PTV Drive & Arrive)
- Up to date developments, e.g. PTV MaaS Modeller

AIMSUN

- Spanish company; 80 employees
- Acquired by Siemens in April 2018
- Two main simulation softwares
- Aimsun.next: All-in-one offering of macroscopic, mesoscopic, and microscopic traffic simulation
- Aimsun.live: Integrated solution for real-time decision making support through forecast simulations
- Simulation based on a car-following model developed by Gipps that focuses on the safe-distance between leader and follower

While PTV and AIMSUN are mainly targeted at commercial use, first insights into traffic simulation software can easily be gained with SUMO.

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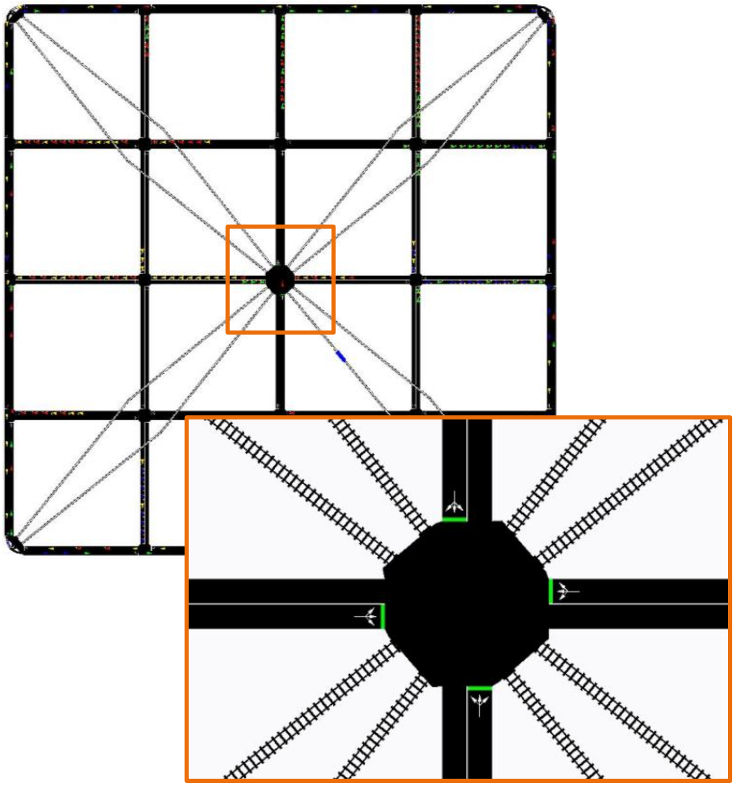
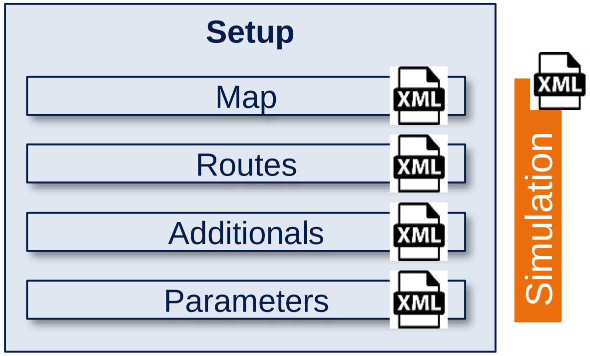
An example of a synthetic simulation network in SUMO

Necessary for the simulation configuration is a road / map network, vehicle or pedestrian routes, and additional configuration parameterization.



» SUMO is implemented in C++ and uses portable libraries
» **Microscopic** approach - vehicles, pedestrians, traffic lights and public transport are modeled explicitly
» Online interaction – control the simulation with TraCI (**Python**)
» Supports many import formats, e.g. **OpenStreetMap**



For real use-cases, the underling road network of cities and realistic OD-matrices for routes are used.

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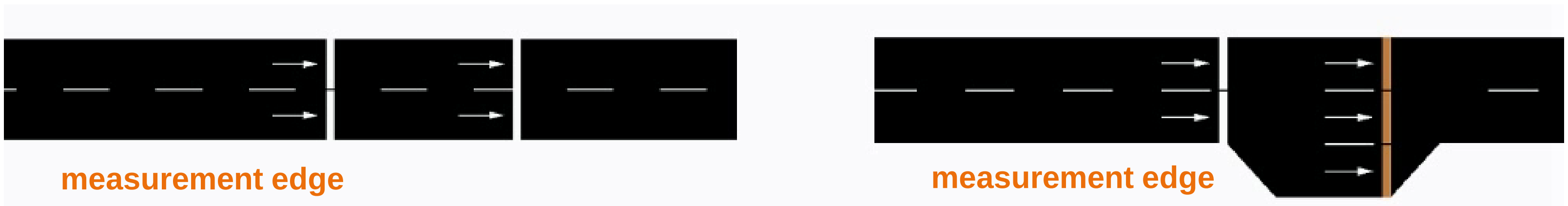
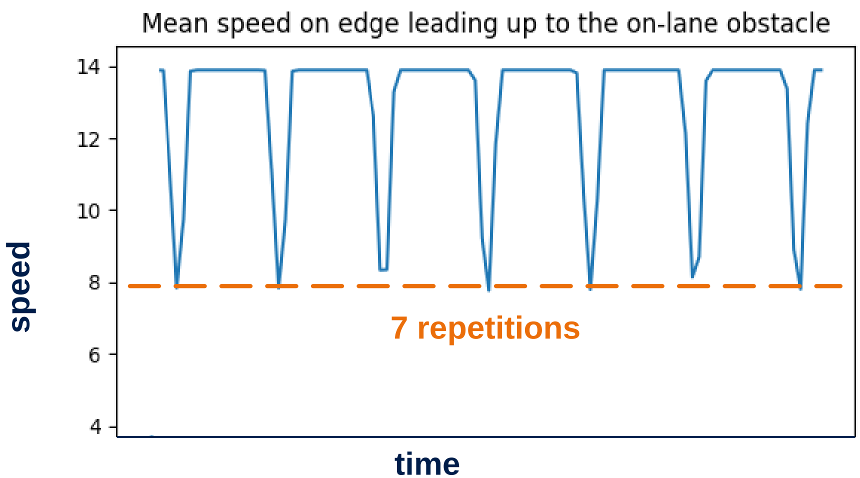
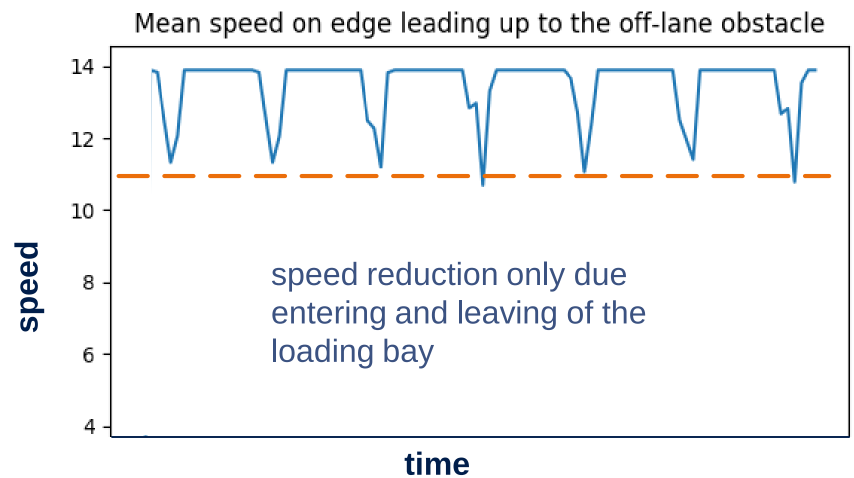
Example of On-Street Parking in SUMO – Can we quantify resulting delays?

In urban environments, traffic is often hindered by on-street parking (e.g. delivery or waste disposal services). We tried to model and simulate the impact of on-street parking on mean system speeds and compared this with the use of additional loading bays.







Parking bays improve free traffic flow at the cost of additional space being used for roads.

Part 3:
Presentation of our Milan 2030 study

Innovative mobility concepts are necessary to provide efficient and ecological mobility solutions– CASE

Challenges

Urbanization
How can the growing individual mobility demand be covered in megacities?

Limited Infrastructure
How can the existing infrastructure be utilized most efficiently?

Pollution
How can innovative mobility concepts counteract pollution and traffic noise?

Inefficient Utilization
How can tailor-made mobility concepts and pricing strategies improve vehicle utilization?

Trends

Connected
IoT for data transfer (V2X), intermodal mobility and user-applications!

Autonomous
Self driving cars / shuttles for optimized driving behavior and security!

Shared Services
Sharing, hailing and on-demand shuttle services for an optimized utilization!

Electric
Environmentally neutral mobility provided through e-mobility from renewable energies!

Milan is facing these challenges especially due to one of the highest rates of private car ownership in Europe

Conditions

Milan is the second-most populated Italian city with 1.35 million inhabitants and about 3.2 million in the metropolitan area.

Everyday during the morning rush hour 850.000 people enter Milan and 270.000 exit the city.

57% of all trips in Milan are taken by public transport, 30% by cars – the particulate matter concentration is one the highest in Europe.

Milan has 50.5 cars per 100 inhabitants, compared to London (31), Berlin (29) or Paris (25).

Actions

From 2008 – 2011 the Ecopass introduced a 8 km^2 traffic limitation zone, resulting in a 30% decrease of vehicles as of today.

From 2012 on more strict regulations were introduced under the name Area C, and an extension of the area to 29 km^2 is planned.

The Sustainable Urban Mobility Plan (SUMP) aims to reshape the overall mobility infrastructure over the next 10 years.

Milan is driving digitalization and aims to provide a Mobility-as-a-Service (Maas) platform solution for a one-app-service.

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Our robo-taxi design around SUMO to solve Milan's traffic problems

Robo-taxis combine the benefits of automation and digitization and shift the focus point of mobility

Recent developments in car sharing, autonomous driving, and the designed effect on urban mobility motivate the study

1 Potentials of car sharing

- » Need-dependent on-demand mobility service
- » Conversion of parking areas into public spaces
- » Reduction of greenhouse emissions

2 Potentials of autonomous driving

- » Increase in traffic efficiency and safety
- » Reduction of mobility-induced emissions
- » Strengthening of Germany's innovative and economic standing

Level 1	Level 2	Level 3	Level 4	Level 5
Driver Assistance	Partially Automated	Automation under Conditions	High-Level Automation	Autonomous Driving
Assisting systems temporarily aid in the cross or lengthwise guidance of the vehicle.	The system temporarily takes over for the cross or lengthwise guidance.	The system takes over the vehicle guidance for a longer period of time.	The system fully takes over the vehicle guidance for a specific application.	The system fully takes over the vehicle guidance in every scenario.

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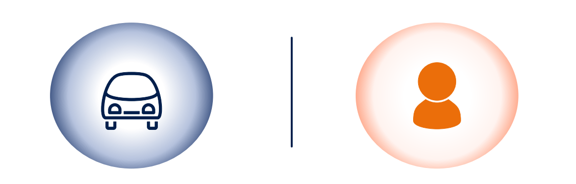
Robo-taxis introduce intelligent communication and shift the focus of mobility to the need of the individual

Innovative mobility concepts shift the focus from individual traffic (theme of the 70’s – “Die autogerechte Stadt”) to individual mobility. Key factors can be highlighted that differentiate classic mobility from the potential of robo-taxis.

» Focus point of mobility



» Availability & Costs

» Parking

» Vehicle capacity

» V2V & V2I Communication

» Distance & speed calibration

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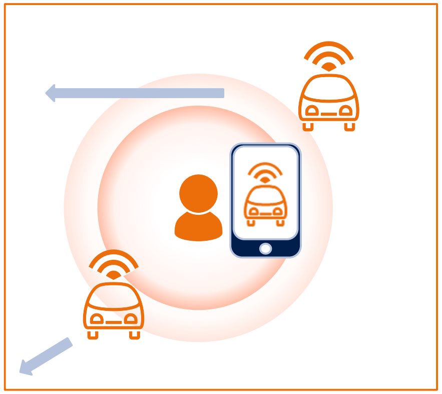
Defining the robo-taxi scheme for our model

1 Identification

- Identify persons that are searching for a robo-taxi
  - Desired travel route
  - Not matched yet
- Identify vehicles with open seats considering passengers and further targeted persons

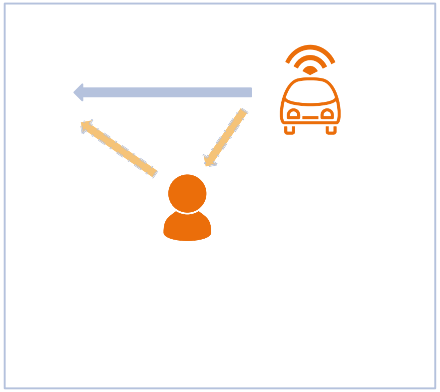
2 Matching

- Match customers to vehicles based on mutual preferences
- Preferences can be basic measures (e.g. distance) or complex scoring systems, including multiple parameters



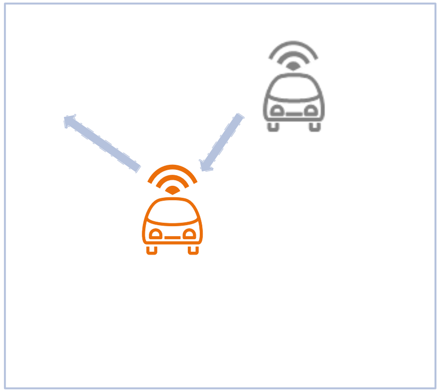
3 Route adaptation

- Efficiently adapt route of the matched robo-taxi considering
  - Existing targets
  - Pick up and drop-off of newly matched person



4 Driving

- Robo-taxi drives new passenger to his target location. At the same time
  - Further passengers can be picked up
  - Other passengers dropped off at their target

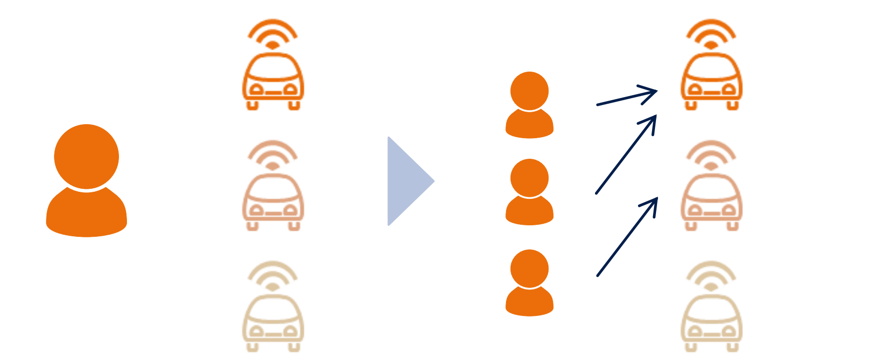


The key step within the robo-taxi scheme is the matching process. We referred to the stable marriage assignment to match persons to vehicles, which allows for a simple implementation.

The stable marriage assignment of unequal sets matches unassigned people to vehicles with free capacity

2a Individual scoring

- All persons with mobility demand individually score the vehicles with free capacity depending on the scoring preference type:
  - Current distance
  - *Waiting time*
  - *Route distance metric*
  - …
- If there are fewer vehicles than persons, the scoring is done for the vehicles and they are later matched to persons



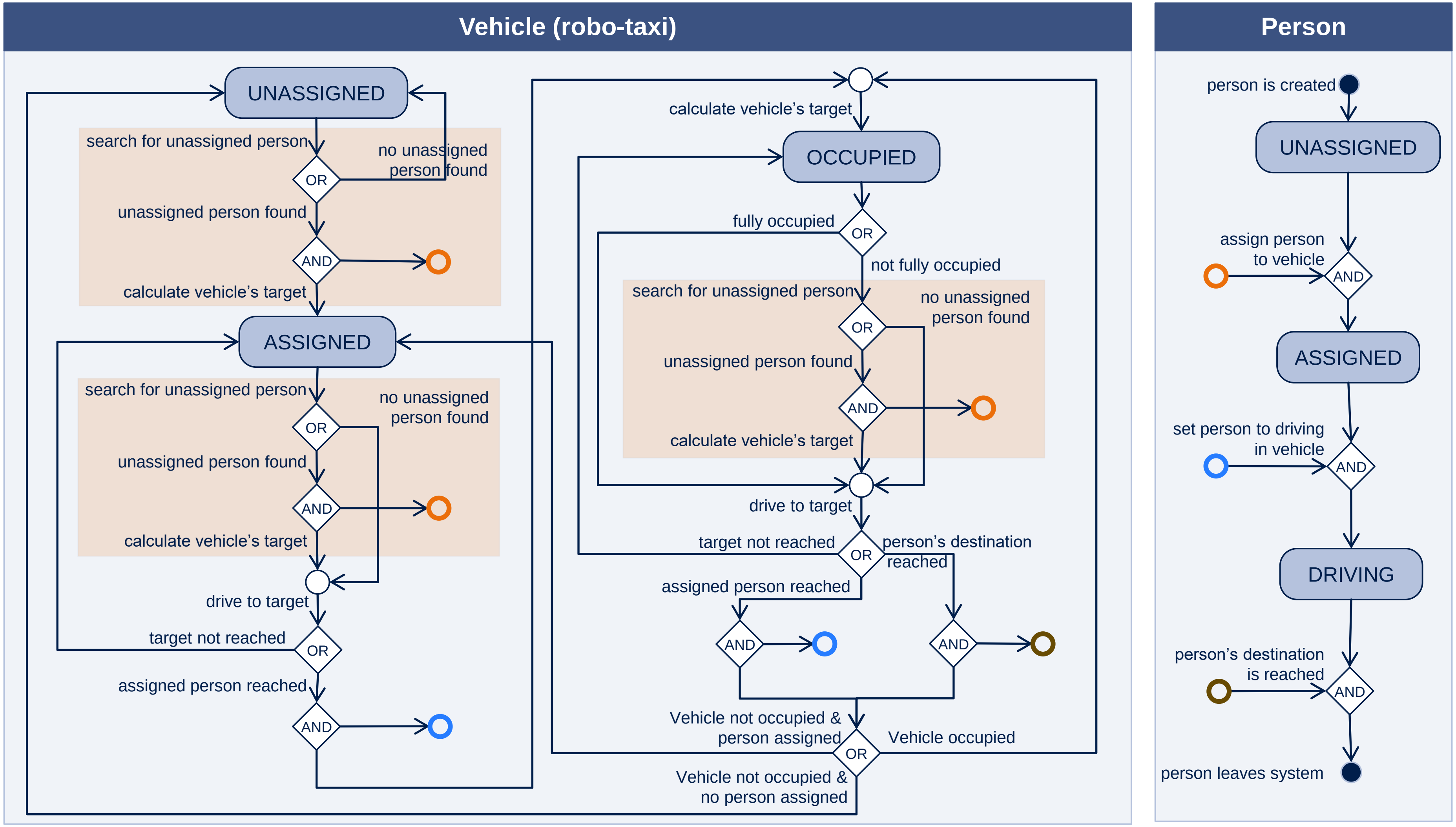
2b Iteration process

- The stable marriage [1] optimization is used to find best pairs between two sets and can be applied to unequal sets. In this use case, people are matched to vehicles, or vice versa depending on the individual quantities
- The algorithm provides an iterative approach for a stable solution
  - The runtime complexity is $O(n^2)$
  - Stability implies that it is not possible for there to be a preferred match between a person and a vehicle, which are not yet paired to each other
- The persons/vehicles are iteratively assigned to their desired choice by respecting strength of preference, i.e:
  - Assign persons to their favored vehicle
  - If vehicle is already matched, person can replace existing match only if the score is more favorable
  - Otherwise the next vehicle is chosen
  - The process is run until all persons have been matched
- *The iteration process could be expanded into the "hospitals/residents problem" in which case a vehicle can be assigned more than one person at once*

Based on the robo-taxi scheme we developed a state diagram to describe the status and transitions of the persons and vehicles in our model.

1) D. G. McVitie and L. B. Wilson: Stable Marriage Assignment For Unequal Sets, 1970

The state diagram for robo-taxis and persons will be the basis for the implementation in SUMO



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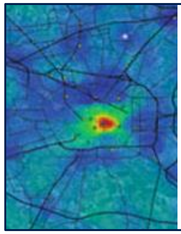
Our robo-taxi simulation is based on the Simulation of Urban Mobility software

» **Map:** The map of Milan was downloaded from **OpenStreetMaps** and converted with NETCONVERT



» **Data:** Time dependent densities where derived from **mobile data** from an open data challenge and calibrated with AMAT traffic data

» **Routes:** Weights from the densities were used as input for the **randomTrips** functionality to derive origin-destination matrices

» **Robo-Taxi:** Robo-taxis were implemented through a custom module via the **Traffic Control Interface**

Robo-Taxi Simulation with SUMO

We complemented the existing functionality around SUMO with a robo-taxi module implemented via the Traffic Control Interface.

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Using randomTrips.py we created routes for persons and vehicles that could be managed by the Traffic Control Interface robo-taxi module

RandomTrips for OD-Matrix

- The analysis of the mobile data is used to create pre-and post-rush-hour densities on a granular grid for the city of Milan
- The densities are converted into weights which are processable by SUMO using the underlying map network
- The weights are normalized with the expected number of commuters and used as input for the randomTrips.py script
- The script stochastically outputs individual routes representing the initial density transition due to rush-hour

```
    $additions = ''

    if ($pedestrian -eq 1){
                            $additions = $additions + "--pedestrians"
                           }
    else                   {
                            $additions = $additions + "--validate"
                           }
    if ($anz -ne 0){
    python $sumoPath\tools\randomTrips.py --net-file $path\maps\$map\netFile.net.xml `
                                          --begin $tbegin `
                                          --end $tend -p (($tend - $tbegin) / $anz) `
                                          --binomial $anz `
                                          --prefix ID$iter- `
                                          --weights-prefix $path\maps\$map\weights\weights$iter `
                                          --route-file $path\maps\$map\routes\route$iter.rou.xml `
                                          --allow-fringe `
                                          -o $path\maps\$map\trips\trips$iter.trips.xml `
                                          $additions
                   }
}
```

Robo-taxi TraCI module

- The robo-taxi SUMO simulation config file is started and also controlled via TraCI
- At every iteration/simulation step, the persons and vehicles are loaded into a cache and the matching algorithm is executed for unassigned persons and vehicles with capacity
- Vehicle routes are adjusted accordingly, and pick-up and drop-off stops are included
- Person and vehicles status are handled according to the designed state diagram

```
def assignPersons2Vehicles(personsUnassigned, vehiclesOpen):

    # get matrix d_ij with d_ij the driving distance between
    vehicleList = [0] + [vehicle for vehicle in vehiclesOpen
    personVehicleList = [vehicleList]

    for person in personsUnassigned:
        person2vehicleDistance = [person]
        for vehicle in vehiclesOpen:
            vehiclePosition = traci.vehicle.getPosition(vehi
            personPosition = traci.person.getPosition(person
            person2vehicleDistance.append(math.sqrt((vehicle
        personVehicleList.append(person2vehicleDistance)
```

The different pre-processing and simulation components were combined in an overall automated process to facilitate the execution.

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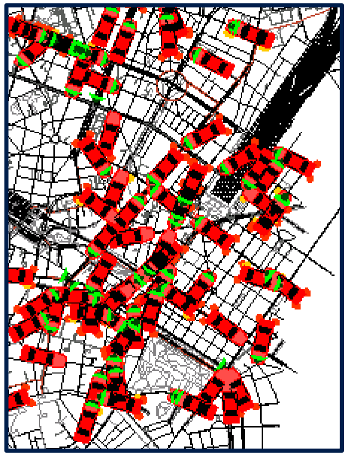
The simulation results

The effect of robo-taxis on traffic in Milan

Rush hour simulation on classic driving and robo-taxis and the evaluation of the quality goals

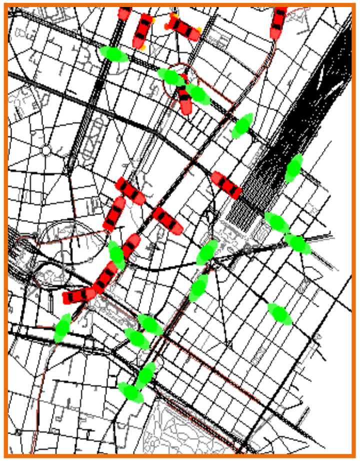


Classic driving:

Unconnected, individually owned, human driven cars

Driving 2030:

Connected, autonomous and shared robo-taxis



A rush-hours simulation will be used to analyze the following aspect of the urban living quality goals by comparing simulation results of the classical driving and the robo-taxi approach.

1	Free traffic flow	What reduction of vehicles is necessary to reach free flow at rush hour?
2	Robo-taxi capacity	What would be the optimal capacity of the robo-taxis? What is the actual usage rate?
3	Robo-taxis	Given an OD-matrix describing the traffic demand, how many robo-taxis are needed?
4	User acceptance	Would the waiting-time for the passengers be acceptable, compared to parking-search?
5	Peak-shaving	What additional effort in reduction of cars and emissions can be expected?
6	Emissions	How big is the expected reduction of emissions on particulates and noise?

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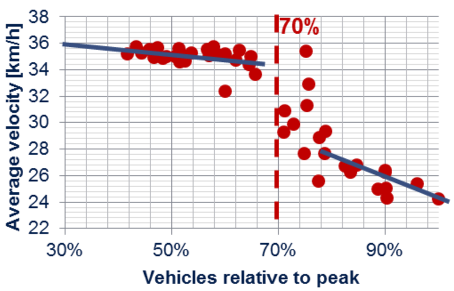
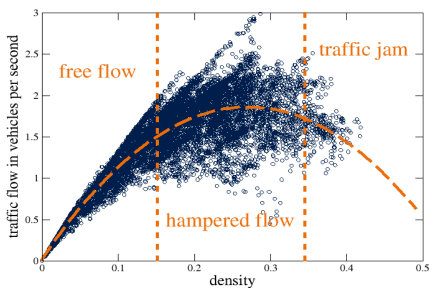
A 30% vehicle reduction is required to reach free flowing traffic at peak rush-hour times

Free-flow vs. congested state

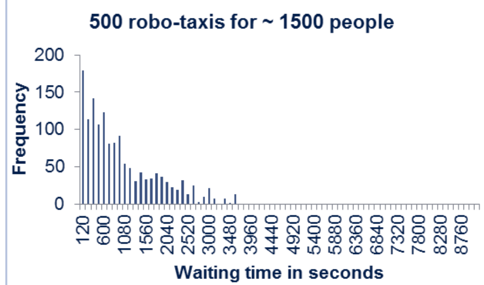
- » Google and AMAT data (averaged over seven sensors) reveal that the number of vehicles has to be reduced by about 30% compared to peak value to reach constant free flow (left)
- » The free-flow and congested states are also seen in the simulation (here 40.000 vehicles were initialized in 2 hours, coming in from the north of Milan)

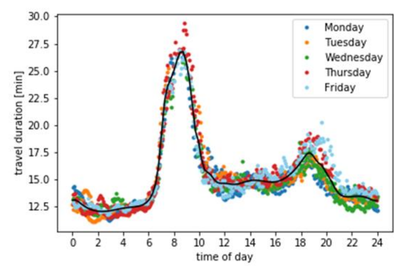




Introducing robo-taxis

- » Assuming an average utilization of 4-5 people per robo-taxi and 1.3 passengers in private cars, between 40% - 50% of the people have to switch to robo-taxi (takes into account that 13% of traffic is cargo)
- » Simulations suggests that waiting times can be feasible considering parking related traffic and search time
- » Peak-shaving of 10% during rush-hour (incentives through pricing models, work concepts, …) can decrease the amount of people that need to transition to around 30%





Inbound traffic on the Viale Fulvio Testi derived from Google Maps data.

Waiting times suggest, that the robo-taxi concept could be accepted by the public. Peak-shaving measures reduce the required transition ratio.

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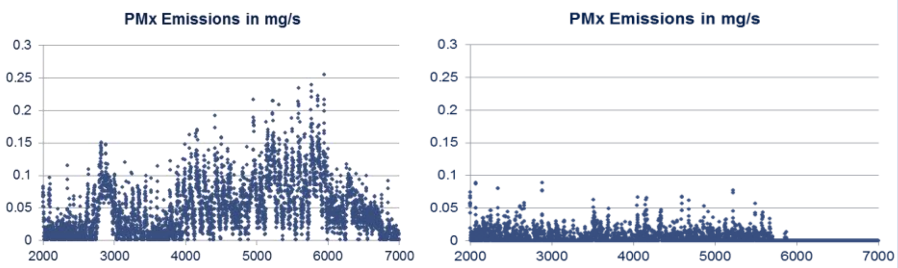
Also, emissions will be reduced far below regulatory thresholds through the introduction of robo-taxis

Reducing emissions

» The relative amount of particulates is dependent on the number of emitting vehicles. In the simulated scenario PM_x emissions are reduce by around 75% (left classical simulation, right only robo-taxis)

» If only half the population switches to robo-taxis with a utilization of 4 persons, we expect emissions to be reduced by almost 40% (50% for electrically powered robo-taxis)

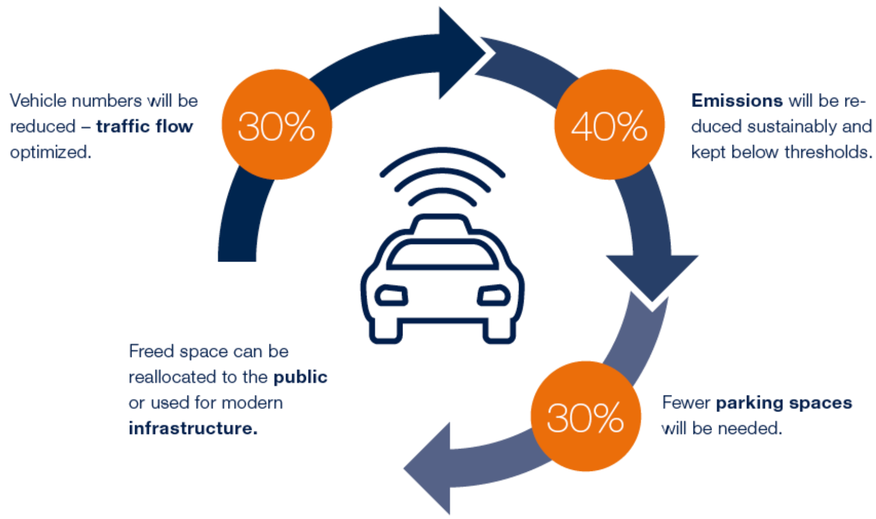
» Further improvements due to freed traffic flow were not considered and could have an added effect



Emissions tracked for 16k vehicles in 2h (left) and 4k robo-taxis (right), driving into Milan from the North.

Summarized

» For the case of Milan we expect to need around 9500 robo-taxis (six seaters) to accommodate 30% of the commuters during rush-hour. This could free traffic from congestion and drastically reduce emissions



When implemented, the robo-taxi concept can improve the quality of life by reducing vehicle numbers and respectively congestions and emissions.

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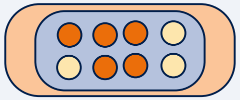
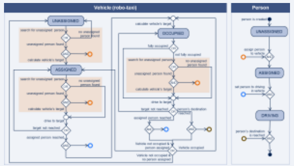
Our Vision to bring robo-taxis alive in Milan

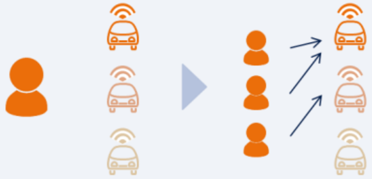
1 Traffic problems in Milan

2 Robo-taxi idea





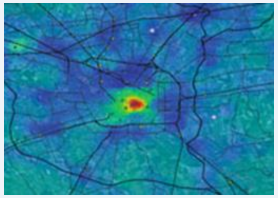
3 Matching-algorithm



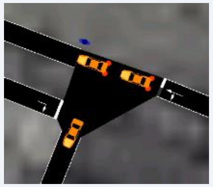
4 TraCI robo-taxi module

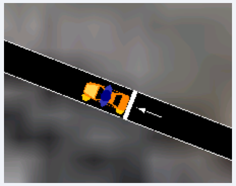
```
def assignPersons2Vehicles(personsUnassigned, vehiclesOpen):

    # get matrix d_ij with d_ij the driving distance between
    vehicleList = [0] + [vehicle for vehicle in vehiclesOpen
    personVehicleList = [vehicleList]

    for person in personsUnassigned:
        person2vehicleDistance = [person]
        for vehicle in vehiclesOpen:
            vehiclePosition = traci.vehicle.getPosition(vehi
            personPosition = traci.person.getPosition(person
            person2vehicleDistance.append(math.sqrt((vehicle
        personVehicleList.append(person2vehicleDistance)
```

5 Routes from mobile data

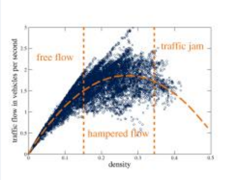


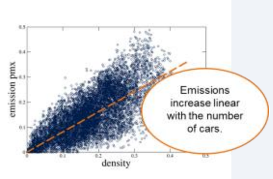
6 Simulation of robo-taxis



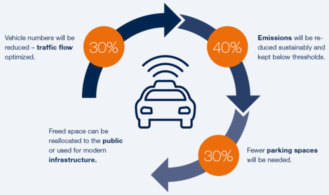


7 Simulation results





8 Benefits for Milan



9 Quick-win implementations

- Use **driver driven robo-taxis** until autonomous driving technology is ready
- Conduct **surveys** and ask the citizens on **mobility preferences**
- Create a **"testing"** area for first implementation
- Develop alternative usage for freed parking **space** and make them **public**
- Increase **reliability** of the transportation system with robo-taxis
- Use **incentives** in order to control peak demand
- Create **incentives** to use shared taxis instead of privately owned cars
- Create an **app** to monitor and control and optimize the mobility demand

We believe that an extended SUMO functionality around the concepts of autonomous driving and shared-services will assist cities in evaluating and establishing innovative and ecological mobility concepts.

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Questions? Comments? – Your contacts!

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