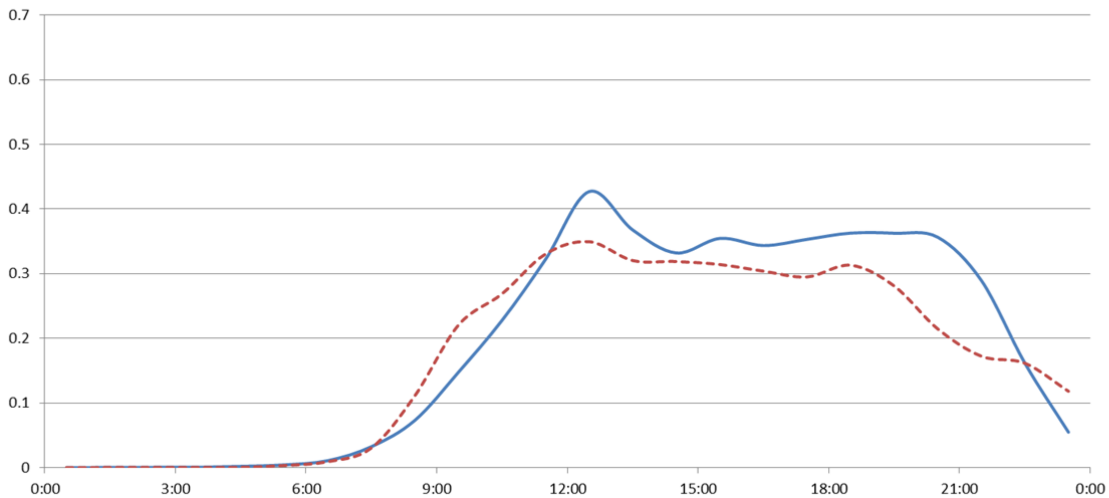

Agent interactions in the activity infrastructure of transport microsimulations

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Abbreviations

FTE	Full-Time-Equivalent
IPF	Iterative Proportional Fitting
LOS	Level of Service
MATSim	Multi-Agent Transport Simulation
NOGA	Nomenclature Générale des Activités économiques
NYBPM	New York Best Practice Model

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Agent interactions in the activity infrastructure of transport microsimulations

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Abstract

This work examines if modelling agent interactions in shopping and leisure infrastructures of the multi-agent transport simulation MATSim increases simulation quality, including destination choice modelling. For that purpose, an agent interaction model is developed that assumes different interaction patterns for four discretionary activity classes. The utility of performing an activity in MATSim is extended by two penalty terms, one penalising agents performing a shopping or leisure activity in locations with very few visitors and the other distributing a penalty for highly crowded activity settings. The agent interaction model is first tested within a synthetic small-scale scenario and then applied to real-world scenario of Zurich.

Results of the synthetic small-scale scenario confirm that the agent interaction model is a valuable tool for implementing agent interaction into MATSim. Validation results of the real-world scenario show that implausibly under- or overloaded facilities are reduced, but further research on the definition of capacities as well as associated side effects is necessary. In particular, the effect of the destination choice module as well as the effect on activity performing times and durations have to be investigated.

Key words

Agent interaction; activity infrastructure; shopping; leisure; MATSim

Preferred citation style

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1 Introduction

It has been known for many years that interaction in transport infrastructure affect traffic flow characteristics (e.g., Wardrop 1952). In a similar way, interaction in activities infrastructure influence people's mobility behaviour. For instance, whereas the presence of other people in bars and party locations might enhance the overall experience and increase utility (e.g., Hui et al. 1991), heavily crowded shops or restaurants may lead to an utility reduction and people might change the destination or revise their time schedule (e.g., Eroglu et al. 1990).

In transport research, common simulation tools incorporate competition for slots on networks, but competition for slots in facilities are only rarely considered. This thesis investigates if modelling interactions in the activities infrastructure of MATSim increases simulation quality, including destination choice modelling for shopping and leisure activities referred to as discretionary activities.

The thesis is structured as follows: First, a short literature review on interaction effects in activities infrastructure is given, followed by a description of MATSim. Subsequently, the agent interaction model is specified and tested within a synthetic small-scale scenario. Finally, model results of a real-world scenario are presented. The thesis concludes with the discussion of the results and considerations that should be taken into account in future research according to the author.

2 Literature review

This section presents a short literature review on agent interaction and agglomeration/competition effects in activities infrastructure and related models which capture those competition effects.

2.1 Agent interaction effects in activities infrastructure

In traffic engineering it was recognized early that interactions in transport infrastructure affect people's route choice. For example, Wardrop (1952) stated that if there are alternative routes which a traffic stream can follow, it may distribute itself over those alternatives due to interaction effects. He defined two criteria which can be used to determine the distribution, either equal journey times or minimum average journey time. Wardrop (1952) showed that, depending on the criterion selected, the traffic flow will distribute itself differently among the alternative routes.

In a similar way, interactions between people in activities infrastructure influence transport decisions. For instance, an activity location such as a restaurant has a certain capacity limit. When this limit is reached, people might look for another location to eat, reschedule their plans, or skip the activity. The following two subsections focus on agent interaction effects in shopping and leisure activity locations. In addition, competition effects for parking lots and agglomeration/competition effects affecting destination choice are discussed briefly.

2.1.1 Shopping infrastructure

Abundant literature can be found on the topic of crowding in shopping infrastructure. Plenty of studies were written from a marketing perspective in order to advise shop operators on how to optimise the shop layout. Harrell et al. (1980) carried out an empirical study of buyer behaviour under conditions of crowding. The authors suggested a model of crowding differentiating between physical density and perceived crowding. Whereas physical density refers to the number of persons in a given space, perceived crowding is subjective to each individual and occurs when high density produces stimulus overload. According to the model, people react to perceived crowding by applying different adaptive strategies (e.g., adjustments in shopping time, deviations in any shopping plans, fewer initiated conversations, etc.) which in turn influences the shopping experience (e.g., store satisfaction).

Eroglu et al. (1986) explored the antecedents and consequences of retail crowding and developed an extended model. Environmental cues (e.g., number of people), shopping motives, constraints (e.g., time pressure) and expectations were identified as antecedents. Regarding the shopping motives, they suggested to distinguish between task-oriented and nontask-oriented shoppers. Task-oriented shoppers are highly interested in making a certain purchase and spend less time per shopping trip. In contrast, nontask-oriented shoppers perceive the shopping activity as a recreational or informational task. Depending on the antecedents, some shoppers judge the environment as being either functionally or dysfunctionally dense (crowding). Functional density may have a positive effect on the shopping experience. Eroglu et al. (1986) mention as an example a nontask-oriented Christmas shopper who finds a highly dense mall very suitable. The authors found the consequences of retail density and crowding perceptions to be complex. The model indicates an influence on the emotional evaluation, on shopper's confidence in having obtained the best value, and on shopping patterns (e.g., different shopping destination).

Based on the model developed by Eroglu et al. (1986), Eroglu et al. (1990) conducted an empirical investigation of the effects and outcomes of retail crowding. Their results indicate that higher retail density leads to more intense feelings of crowding and less satisfaction with the shopping environment. Eroglu et al. (1990) also observed that task-oriented shoppers experienced more retail crowding than did nontask-oriented shoppers in a highly dense setting.

Hui et al. (1991) examined the effects of consumer density (physical dimension) and consumer choice on the service experience. The examination included the development of a model that highlighted the importance of perceived control and an experimental test that analysed the stated hypotheses. Perceived control is understood as one's perception of the behavioural, cognitive and decisional control in the interaction process. The model assumed that consumer density and consumer choice influence person's perceived control which in return affects the emotions and the perception of crowding. The experimental study was based on a questionnaire and included two service settings, a bank and a bar. The authors expected that consumer density has a less negative impact in a bar environment than in a bank environment. The results of the experiments confirmed the approach. Perceived control can be used to explain the consumer's reactions to consumer density. Additionally, it is shown that a highly crowded bar is perceived as less unpleasant than a highly crowded bank. This supports the hypothesis that the relationship between density and pleasure varies between different service settings.

Baker et al. (1994) explored the effects of specific store environment factors on quality interferences. The study also analysed the mediating effect of merchandise and service quality on store image. Regarding the store environment, Baker et al. (1994) differentiated between ambient factors (e.g., lighting), design factors (e.g., shop layout), and store social factors (e.g., number of other customers). The study used sales people to represent the social factor. A prestige-image social environment had more and better dressed store personnel than a discount-image social environment. The results showed that the store image also influences the perception of crowding. For example, if a prestige-image shop is understaffed, customers may already evaluate the service quality and shopping experience negatively even if there are only few customers in the store and no (physical) crowding condition is apparent. Similar findings were presented by Machleit et al. (2000). In their study, the relationship between perceived crowding and shopping satisfaction also varied by store type.

Dion (1999) distinguished between the social (number of people) and spatial (amount of space) dimension of density. Results of a field study and a laboratory experiment indicate that their impact on crowding is not the same. Whereas social density leads to aggressive behaviours (e.g., force the way through the crowd), spatial density promotes self-blame reactions (e.g., for choosing rush hour time) and reduces opportunism (e.g., look for promotions and good deals).

Michon et al. (2005) investigated the interaction effects of the mall environment (e.g., ambient odours) on the shopping behaviour under various levels of retail density. In their field study, they noticed that shoppers' profile were significantly different during low, medium and high retail density periods. In addition, they found that the effect of density on the shoppers' mood and perception may be similar to an inverted U shape. An empty store might be just as unfavourable as a very crowded one.

Eroglu et al. (2005) conducted two studies to examine the role of shopping values. Two types of shopping values were differentiated, utilitarian values (whether the purchase goal is achieved) and hedonic values (experiential worth of shopping trip). A task-oriented shopper might attach more importance to the utilitarian value whereas a nontask-oriented shopper might emphasise hedonic values. According to their results, perceived retail crowding appeared to affect shopping values, albeit not very strongly. These effects were guided by shoppers' emotions which mediated the effect of spatial crowding on shopping satisfaction. The results indicate that crowding may positively affect shopping satisfaction. Eroglu et al. (2005) observed a similar inverse U relationship between crowding and satisfaction as Michon et al. (2005). The authors assumed that extremely uncrowded or extremely crowded states might produce undesirable states of over- and under-arousal, respectively.

Pan et al. (2011) analysed the different effects of retail density and time-pressure in a goods and service setting. The analysis of shoppers' store attitudes and behaviour in a good setting revealed a curvilinear pattern as the level of retail density increases (inverted U shape). This finding is in line with Michon et al. (2005) and Eroglu et al. (2005). In contrast, examinations in a service setting revealed a rather linear than curvilinear relationship between retail crowding and shopping behaviour, except under conditions of time-pressure. In addition, the authors found the optimal level of crowding to depend on the type of service setting which is consistent with previous studies (e.g., Hui et al. 1991).

2.1.2 Leisure infrastructure

Contrary to the extended research in the field of crowding in shopping infrastructure, there is less literature on the effects of people interaction in leisure infrastructure. Several studies have addressed the field of carrying capacities of outdoor and extra-metropolitan recreational settings such as parks and forests (e.g., Shelby et al. 1984; Manning et al. 1999; Fleishman et al. 2009). Manning et al. (1999) defined carrying capacity as the maximum amount and type of visitor that can be accommodated appropriately within a recreational area. Associated concepts try to assess carrying capacity by formulating a set of indicators and quality standards of the visitor experience (social dimension) and resource conditions (resource dimension) (e.g., Stankey et al. 1986). A widely used indicator is the number of encounters with other visitors per day (Manning 2007). Recently a level-of-service approach has been introduced (Fleishman et al. 2009). This approach uses overall user satisfaction as the main criterion for assessing the level of service which is understood as a basic attraction- or detraction-factor for potential users to a system. As they pointed out, there is no single clear benchmark for carrying capacity, it is dependent on person's objectives and associated measurable indicators.

Agent interactions in metropolitan leisure infrastructure such as restaurants, bars, museums, or libraries are less often treated. Eroglu et al. (1986) mentioned that functional density may have positive effects. Some participants of their study reported "that they visited malls simply to watch others" (Eroglu et al. (1986), S.357). Those trips have to be counted as leisure activities rather than shopping activities. In this case, people look for higher levels of social stimulus, and interactions with other visitors have a positive effect.

As mentioned in section 2.1.1, Hui et al. (1991) examined the effects of consumer density in a bank and a bar setting. The examination in a bar setting revealed that crowdedness produced positive emotional and behavioural effects.

An observational case study of baseball spectators in a stadium was conducted by Holt (1995). Based on observations of nearly 80 games during a time span of two years, Holt developed a typology of consumption practices. He suggested to use four aspects in order to explain why people consume:

- Consuming as experience: accounting, evaluating, and appreciating
- Consuming as integration: assimilating, producing, and personalizing
- Consuming as classification: through objects and actions
- Consuming as play: communing, socializing

In communing, spectators share their experiences with each other. In socializing, they use their experiences to entertain each other. The presence of other spectators therefore enhances the overall act of consuming.

Eastman et al. (1997) analysed public sports viewing in bars and restaurants. Through observations and interviews they identified four schemas for explaining public sports viewing: participation in a community, social interaction opportunity, access to unobtainable events, and diversionary activity. The authors noticed that people used public sports viewing bars and restaurants for social interaction (e.g., talk to strangers) what is in line with the findings of Holt (1995).

Pons et al. (2006) studied consumer reactions in a dense (hypothetical) leisure setting, namely in a disco. In addition, they investigated the influence of cross-cultural differences between North America and the Middle East. The analysis of consumers' reaction confirmed the existence of an overall positive relationship between perceived density and consumers' evaluation of the disco experience. In this leisure setting, crowding appeared to positively affect the service experience. Further results revealed that the effects of perceived density vary across cultures. North American people perceived the service setting as being denser than Middle Eastern people.

2.1.3 Parking infrastructure

Agent interactions do not only occur in the activity infrastructure itself, but also in the surrounding infrastructure. For instance, parking types, search times, and costs significantly influence travellers' decisions (Weis et al. 2011).

Van der Waerden et al. (1998) studied the impact of the parking situation in shopping centres on store choice behaviour at a micro level. The authors estimated and validated a hierarchical logit model of parking lot and store choice behaviour. They assumed that the store choice is related to the parking lot choice. Before-and-after data of supermarket visitors of a regional shopping centre in the Netherlands were used. Model estimation using the before-data showed that the following attributes influenced the utility of the parking lot and supermarket choice:

- Increase of utility:
  - Location of the parking lot vis-à-vis the origin of the consumer
  - Availability of supermarket trolley facilities at the parking lot
- Decrease of utility:
  - Higher distances between supermarket and parking lot
  - Number of parking spaces per parking lot

Interestingly, the parameter for the number of parking spaces per parking lot was negative. The authors assumed that consumers tended to depreciate large parking lots in order to avoid long walking distances. Validation with the after-data (after changes in parking infrastructure) revealed that the model is not able to reproduce the validation data at an acceptable level. Therefore, the model presented needs further refinements.

Weis et al. (2011) conducted a stated choice survey on the influence of parking availability on destination and mode choice of travellers in Switzerland. The estimated models fitted very well. Results showed that the parking characteristics impact destination and mode choice. According to the models, respondents preferred parking in a garage to on-street and open parking. In addition, performing shopping and leisure activities in a city centre rather than in the outskirts proved to be more attractive. The utility of a location increased with low pricing levels and a good cost-performance-ratio. Renouncing an activity due to excessive search for a parking space or an appropriate location was perceived negatively. The willingness-to-pay for reducing parking search times was high for very short activities, and steeply decreased as the activity duration rose.

2.1.4 Agglomeration/competition effects

Destination choice is also affected by interaction effects between activity locations themselves. The spatial pattern and structure of activity locations influences peoples' destination choice. Fotheringham (1983a) suggested that destination choice may be viewed as a result of a two-stage decision-making-process. First, people choose a broad region and in a second stage, they choose a specific location from the set of destinations within the broad region. Therefore, the configuration of destinations around an origin is relevant. Fotheringham (1983a) stated that a higher accessibility of a destination to all other destinations in a spatial system leads to a reduced likelihood that that destination is a terminating point for interaction from any given origin, ceteris paribus. The author revealed that common gravity models have an undesirable spatial-structure effect in estimated distance-decay parameters. Instead of purely reflecting behavioural patterns, the distance-decay parameter shows to be dependent on the configuration of destinations (Fotheringham 1983b). Fotheringham (1983a) proposed a new interaction model, the so-called competing destination model. This model includes a variable that captures the accessibility of a destination to all other destinations. In this manner, the interaction behaviour of a two-stage decision-making process is appropriately modelled.

Fotheringham (1983b) further analysed the misspecification of production-constrained gravity models under the presence of competition or agglomeration effects. The author quoted grocery shopping as an example where competition effects may be apparent. Grocery stores in relative isolation may be able to gain more customers than if they were closer to similar stores. In contrast, consumer-goods stores may be more successful when they are clustered, rather than being distributed dispersedly in space. If the accessibility parameter in the competing destination choice model is positive, then agglomeration effects are present, a negative accessibility parameter indicates that competition forces are involved (Fotheringham 1985). Fotheringham (1985) showed that the competing destination model is also able to model the situation where subgroups of facilities exist and where, within the same or different subgroup, various spatial competition and agglomeration effects are present.

Fotheringham et al. (2001) conducted a simulation experiment on hierarchical destination choice and demonstrated the inability of common gravity models to model traffic flows accurately when such flows result from a hierarchical decision making process. The authors also tested competing destination models which showed to model the underlying process more accurately. Results of the simulation experiment indicated that the accessibility parameter is robust enough to capture both agglomeration and competition effects.

2.2 Models with competition effects

Models that consider competition effects generated by a given demand in a limited infrastructure are rare. For example, de Palma et al. (2006) incorporated infrastructure competition effects for residential destination choice on a household level. Vrtic (2005) developed a model that solves a route and mode choice problem simultaneously. This concept allows route capacity constraints to be accounted for when modelling both route and the mode choice.

In the following section, a short overview of existing destination choice models taking agent interaction effects into account is presented. The presentation concludes with a detailed description of the destination choice model of MATSim which is the basis for the work of this thesis.

2.2.1 Existing destination choice models

Vovsha et al. (2002) presented the technical application of destination choice constraints based on the NYBPM, a microsimulation demand-modelling system for the New York – New Jersey – Connecticut metropolitan area. The NYBPM proceeds as follows: First a journey-frequency choice model produces a file containing all journeys, then the destination choice model attaches a destination zone to each record, and finally mode choice is applied. Destination choice is based on household and individual characteristics, attributes of the known origin zone, and calculated origin-destination impedances. One by one, destination choice utility is calculated for each origin-destination pair and a Monte Carlo random pick is performed. Destination choice capacity constraints are introduced by generating purpose-specific zone attractions. Ensuing, balancing is carried out by filling out a production-attraction matrix where every production (journey) has to be assigned to a specific attraction. Selected attractions are removed and the probabilities of choosing various destinations are periodically updated. In this manner, zones that have not lost attraction gradually become more attractive. A constraint parameter is defined in order to dictate how the production-attraction matrix is filled. If the purpose is fully constrained (e.g., work, school), the constraint parameter is 1, consequently every single attraction is chosen. Relaxed constraint purposes are assigned with a value greater than 1. In the NYBPM, maintenance and discretionary journeys were relaxed constrained with a constraint parameter of 1.5 to 2. A disadvantage of this sequential procedure is the so-called last-record problem. Towards the end, only few attraction zones remain open and they have to be assigned to the remaining productions regardless of accessibility. This leads to very long journeys for records that are processed last. Relaxed constrained purposes are less affected by this problem.

Waraich et al. (2011) developed an agent-based parking choice model that takes destination interaction effects into account. As a simplification, the parking search process is left out. Four parking types were differentiated: public parking, private parking, reserved parking (e.g., for disabled people), and preferred parking (e.g., parking space with a power outlet for people driving electric vehicles). A parking choice utility is introduced to allow agents to compare different parking spaces. The parking choice algorithm makes decisions on two levels and is hierarchical. First, the general set of parking spaces is defined based on the parking supply (parking occupancy, reserved/private parking available, and agent's preferences). Then a score is assigned to all parking spaces according to the parking choice utility function and the parking space with the highest score is selected by the agent. Waraich et al. (2011) added the model as a separate module to MATSim. A description of MATSim is given in section 3. The utility function in MATSim is extended by the parking utility term mentioned above. The parking choice algorithm is able to run parallel to the MATSim traffic simulation which saves computation time. A couple of post-processing changes to the agent's plan in MATSim were necessary (Waraich et al. 2011). After the implementation, a scenario of the city of Zurich was simulated. Results indicated that the model captured key elements of parking, such as parking capacity and pricing. An interesting feature of the described parking choice model for this thesis is the possibility to use the parking utility score as an external feedback for the destination choice model. For instance, if the parking supply surrounding a shopping centre is lower than demand, some people might have to walk long distances between parking and destination and therefore choose another shopping destination.

Marchal et al. (2005) proposed a model for destination choice for discretionary activities assuming that the agents are interconnected by a social network through which they can exchange information. This approach further proceeds on the assumption that agents only have limited information about a small subset of the overall spatial environment. Iteratively destination choice is performed through applying a learning mechanism where agents exchange information through their social network. For a detailed description please refer to Marchal et al. (2005).

In addition to the parking choice model, MATSim includes a destination choice module. There are three basic approaches available for destination choice. The most basic approach applies random search which leads to very slow convergence. Within the framework of the second approach, Horni et al. (2009a) improved the destination choice module by integrating a time-geographic approach based on Hägerstrand's time geography (Hägerstrand 1970). Activities were classified as fixed (e.g., work) or flexible (in this model, shopping or leisure). In the destination choice step, the spatial and temporal dimension of the fixed activities were taken as fixed and thus defined the origin and terminal vertex of the space-time prisms confining the flexible activities. In addition, it was assumed that the duration of the flexible activity was fixed as well. In this manner, the travel time budget for a flexible activity could be computed. Then a distance-based approximate subset of locations is constructed by drawing a circle whose centre is the point equidistant to the two fixed locations and with a radius depending on the travel time budget and travel speed. Subsequently, a destination is randomly chosen from the subset and the feasibility in relation to the given travel time budget is checked. If the travel time satisfies the travel time budget, the flexible activity location is taken as a first anchor point. If the travel time budget is exceeded, the initial travel time is changed. Then another destination is chosen randomly and tested again. After a certain number of failed trials, the algorithm terminates by randomly choosing a destination from the universal choice set.

Besides implementing the time-geographic approach described, Horni et al. (2009a) applied capacity restraints in order to improve behavioural realism. The activity utility function is multiplied by:

$$\max(0; 1 - f_p) \times f_{attractiveness}$$

where,

$$f_p = \text{penalty factor, and}$$

$$f_{attractiveness} = \text{attractiveness factor}$$

The first term penalises agents dependent on the load of the location and is modelled as a power function. The second term is an attractiveness factor and is set proportional to the location size. For demonstration purposes, Horni et al. (2009a) only apply capacity restraints to shopping infrastructure and the capacities of all shopping facilities are set equal, in such a way that they satisfy the total daily demand with a reserve of 50%. The capacity restraint function for location *i* has the following form:

$$f_{p,i} = \alpha_i \times \left(\frac{load_i}{capacity_i}\right)^{\beta_i}$$

where,

$$\alpha_i = 1/1.5^{\beta_i},$$

$$\beta_i = 5, \text{ and}$$

$$f_{p,i} = \text{penalty factor}$$

Horni et al. (2009a) tested the described implementations with a simulation scenario for Zurich. According to the results, the time-geographic approach showed to be productive. Furthermore, the model with capacity restraints improved behavioural realism. The number of implausibly overloaded locations was reduced. Nonetheless, the local search method described above leads to an underestimation of total travel demand (e.g., too-short travel distances) because flexible activity trip distances keep decreasing over the iterations (Horni et al. 2009b).

The third approach was developed by Horni et al. (2011b). By adding unobserved heterogeneity to the utility function through a random error term, Horni et al. (2011b) corrected for the underestimation of total travel demand. Thereby, MATSim got fully compatible with discrete choice theory. Unobserved heterogeneity is subjoined with a fixed individual error term per person-alternative-pair what is called quenched randomness. This means that all randomness is computed initially for each person-alternative-pair and does not evolve with time. As Horni et al. (2011b) have shown, under the assumption of equal activity time, maximum potential travel effort is accepted for reaching the destination with the largest error term. Additionally, it can be assumed that an activity is dropped if it does not generate positive utility at least for one destination and that a person only travels farther if that effort produces a net benefit given by the error term. Since linear travel distances are used as travel disutilities, the upper bound for maximum search space for person p, activity q and monetary cost m is given by:

$$distance_{pq}^{max} = \frac{\epsilon_{\omega pq}[\quad]}{\beta_{distance,pq}\left[\frac{1}{m}\right]},$$

where,

$\epsilon_{\omega pq}[\quad]$ = largest error term (location ω) and

$\beta_{distance,pq}\left[\frac{1}{m}\right]$ = individual distance cost coefficient

Hence the radius of the circle for the search space is defined as follows:

$$r_{\Gamma_{pq}} = \left(distance\left(l_{pq-1}, l_{pq+1}\right) + distance_{pq}^{max}\right)/\psi$$

where,

$distance_{pq}^{max}$ = upper bound for maximum search space,

l_{pq-1} = preceding activity location,

l_{pq+1} = succeeding activity location, and

ψ = choice set size parameter

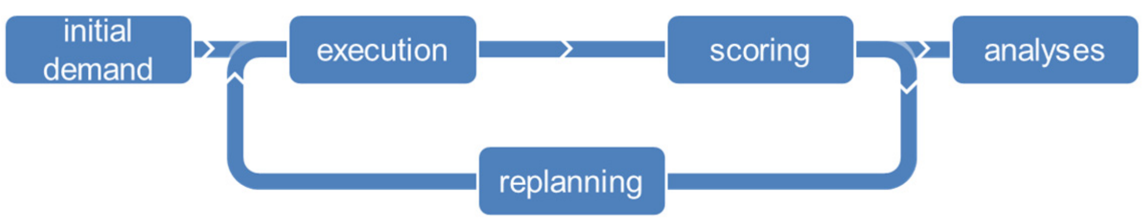
The choice set size parameter is currently set to 2. Once the search space is defined, a probabilistic best response is applied. For the search space destinations, travel times are estimated and a score is assigned. Subsequently, a random choice weighted by these scores is performed. For computational reasons, the choice set is arbitrarily restrained to the 30 destinations with the highest score. Simulation results for Zurich indicate that adding unobserved heterogeneity substantially improves the destination choice module of MATSim.

3 MATSim

MATSim is an agent-based traffic microsimulation framework designed for large-scale scenarios. It is implemented in JAVA, open source, and consists of several modules which can be combined or used stand-alone. An example of such a module is the destination choice module described in section 2.2.1. MATSim uses an activity-based demand generation where based on census data and other surveys a sequential list of activities and trips connecting these activities for every person in the study area is produced. In this manner, transport demand is derived from daily activity patterns and therefore it is possible to ensure temporal and spatial consistency of travel behaviour (Meister et al. 2010). Consequently a synthetic population of individual agents with appropriate activity, demographic, and travel characteristics is generating by using IPF and Monte Carlo techniques as detailed in Frick et al. (2004).

Based on this initial demand, every agent iteratively optimizes its daily activity chain in competition for space-time slots on transportation and activities infrastructure with all other agents through a co-evolutionary approach. The basic process steps of MATSim are illustrated in Figure 1.

Figure 1 Basic process steps of MATSim



Source: Balmer et al. (2010)

The initial demand is generated as described above. In addition, MATSim provides corresponding supply models, such as street network and facilities. Facilities are an artificial construct that describe buildings. They aggregate all buildings in certain area (usually in a specific hectare) and are connected to exactly one network link. After the generation of the initial demand, a co-evolutionary algorithm consisting of the three steps execution, scoring, and replanning is applied. Every agent has an own population of plans, i.e. a fixed number of day plans memory. Each day plan consists of a daily activity chain and an associated utility value.

In the execution step, agents select one daily plan out of their population of plans according to a certain model (e.g., a logit distribution) and execute this plan, i.e. the network loading is performed. The mobility simulation of MATSim belongs to the group of microsimulations and is based on an event-driven queue model described in Meister et al. (2010).

In the scoring step, a utility value (so called "score") is assigned to each plan according to a certain utility function. The basic utility function in MATSim is defined in Charypar et al. (2005) and is based on the Vickrey model for road congestion which takes departure time choice into account (Vickrey 1969; Vickrey 1971). The utility of a plan is determined by the sum of all activity utilities and the sum of all travel (dis)utilities:

$$U_{plan} = \sum_{q=1}^{n} U_{act,q}\left(type_q, start_q, dur_q\right) + \sum_{q=2}^{n} U_{travel,q}(loc_{q-1} - loc_q),$$

where,

$U_{act,q}$ = utility of activity q

$U_{travel,q}$ = utility of travel for activity q,

$type_q$ = type of activity q,

$start_q$ = start time of activity q,

dur_q = duration of activity q,

loc_{q-1}, loc_q = location for activity q-1 and activity q, respectively

A detailed description of the utility function and its associated parameter setting is given by Charypar et al. (2005).

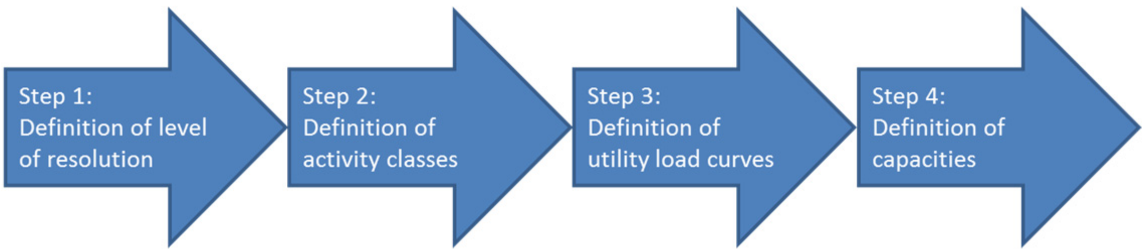
In the replanning step, a certain share of agents (usually 10%) is allowed to mutate a selected plan, clone a selected plan, or cross a selected plan with another plan. The replanning modules define the search space where ideally randomness should be dispensed. Due to the huge search space and in order to increase the convergence speed, certain heuristics and best-response approaches are applied. Current search space dimensions in MATSim are route, time, mode, and destination choice. If an agent ends up with too many plans, the plan with the lowest score is removed from the agent's population of plans.

The goal of each agent is to maximise the utility of its daily plan. Through replanning daily plans and eliminating plans with low utility scores an optimisation process is employed that corresponds to the principle of the survival of the fittest, or more precisely of the non-survival of the non-fittest. The described co-evolutionary algorithm is repeated until systematic relaxation is reached. This point may correspond to an user equilibrium, called relaxed demand.

4 Agent interaction model

The model specified in the following focuses on interaction in shopping and leisure infrastructures. Parking and agglomeration/competition effects are not incorporated for simplification at this point. The modelling approach is divided into the four main steps shown in Figure 2. These four steps represent the challenges that have to be resolved in order to model agent interaction in activities infrastructure.

Figure 2 Modelling approach



First of all, the appropriate conceptual resolution has to be defined. It is of great importance to clarify the level of resolution because all other problems are dependent on it. In a second step, the activity classes that need to be differentiated have to be defined. Thereupon, the shape of the utility load curves and the capacities of the activity locations can be determined. Below, a section is written to each step, starting with the level of resolution.

4.1 Level of resolution

MATSim belongs to the group of disaggregated microsimulations, but still the appropriate resolution for modelling agent interaction in the activities infrastructure remains an open question. In contrast to macrosimulations, microsimulations have the advantage of a high theoretical, spatial and temporal resolution (Wegener 2011). They make it possible to explicitely formulate chained decisions and time-space constraints on individual travel behaviour (Vovsha et al. 2002). In addition, microsimulations such as MATSim allow for the simulation of large-scale scenarios but there are a few barriers for upscaling small-scale findings for large-scale application in microsimulations. According to Horni et al. (2012), main upscaling barriers are limited data availability, computational difficulties, and an implementation backlog.

Sometimes, the explicit modelling of variability of travel demand in microsimulations may be considered as a problem, but in other cases, it might be more advantageous. For instance, it might be more useful to estimate the expected range of likely traffic volumes when planning a certain road infrastructure than relying on average daily or hourly volumes (Vovsha et al. 2002).

When modelling agent interaction in activities infrastructure, a trade-off between required conceptual resolution on one side and available data as well as acceptable computational time on the other side has to be found. It is important to look on the one hand at the characteristics and determinants of agent interaction and on the other hand at the available data simultaneously. The characteristics and determinants specify the different activity classes that have to be differentiated in order to accurately model agent interactions. Since the available data may limit the resolution, it has to be considered. In addition, it is important to keep an eye on variability issues.

4.1.1 Determinants of agent interaction in the activities infrastructure

A summary of the determinants of agent interaction in activities infrastructure based on the literature review is given in Table 1. The estimated magnitude of influence is indicated by the number of positive signs.

Table 1 Determinants of agent interaction in activities infrastructure

Category	Subcategory	Influence	Related literature
Individual's attributes	Age	+	Pons et al. (2006)
	Culture	+	Pons et al. (2006)
	Constraints (e.g., time-pressure)	++	Eroglu et al. (1986)
	Motives (e.g., nontask-oriented)	++	Eroglu et al. (1986)
	Expectations	+	Machleit et al. (2000)
	Tolerance level	+	Pons et al. (2006)
Activity type		+++	Hui et al. (1991)
Infrastructure attributes	Infrastructure type (e.g., garden centre vs. greenware)	++	Hui et al. (1991)
	Location size	+++	Eroglu et al. (1986)
	Atmosphere (e.g., odor or lighting)	+	Michon et al. (2005), Dion (1999)
	Manning level	++	Baker et al. (1994)
	Prestige	+	Baker et al. (1994)

Obviously, agent's individual attributes influence the interaction process. In addition, the activity type is a very important determinant and clearly has to be considered. For instance, agents may react to crowding very differently in the same infrastructure type depending on the respective activity they perform. In the same shop, a task-oriented shopper and an agent that went shopping as a recreational activity evaluate crowding very differently. Infrastructure attributes have to be accounted for as well. Mainly the location size is important as it defines the capacity.

Some determinants are interrelated. Constraints such as time-pressure may lead to a lower tolerance level, or the motives may affect the expectations.

4.1.2 Data

The resolution of the data relating to people's activity behaviour is different for supply and demand. Most of the data is provided by the Swiss Federal Statistical Office.

Supply side

On the supply side, a very high data resolution in the context of different infrastructure types exists. Activity locations are derived from the Federal Enterprise Census 2001 Sectors 2 and 3 (Swiss Federal Statistical Office 2001). This survey collects data on all private and public businesses and workplaces in the second and third sector using NOGA-1995-classification. NOGA is a tool for classifying businesses and workplaces according to their economic activity and arrange them in coherent groups (Swiss Federal Statistical Office 2011a). Approximately 1'000 attributes related to employment (both full-time and part-time) and NOGA commercial types are aggregated on a hectare level or stored as presence-codes. Every workplace is assigned with a size category, an industry category, the number of employees, and the level of employment. In addition, all workplaces are geocoded and linked with a building in the Federal Register of Buildings and Dwellings (Swiss Federal Statistical Office 2012).

There is less information on infrastructure attributes such as location size, atmosphere and manning level. From the Federal Enterprise Census only information on employment is given. Some trade organisation, e.g., Gastrosuisse for gastronomy, provide more detailed information on average number of seats of restaurants etc. In the Federal Register of Buildings and Dwellings more information is given on the buildings where workplaces are located. The list of attributes in the register includes the building area and the number of floors (Swiss Federal Statistical Office 2009). Nevertheless, the declaration of the building area is not mandatory. Therefore, the data set is incomplete and the building area is known for only few buildings.

Demand side

Table 2 shows the resolution for shopping activity types on the demand side based on the Microcensus 2005 (Swiss Federal Statistical Office 2007). The Microcensus is a statistical survey of the population's travel behaviour on a household level that is conducted about every five year. The survey deals with questions about vehicle ownership, possession of driver's licences and/or public transport travel cards, daily travel patterns (number of trips, duration of trips, distances travelled), purpose of trips and means of transport used, one-day excursions and excursions with overnight stays, and views regarding Swiss transport policies (Swiss Federal Statistical Office 2007).

Table 2 Activity types for shopping trips in Switzerland according to Microcensus 2005

Activity type	Share of total trips [in %]
Grocery	67.6
Consumer goods	7.8
Shopping as a recreational activity	7.5
Grocery and consumer goods but not shopping as a recreational activity	6.3
Others	4.9
Investment goods	2.7
Shopping as a recreational activity combined with other yes answers	2.1
Other combinations	1.1
Total	100

Source: Swiss Federal Statistical Office (2007)

Grocery shopping accounts for more than two thirds of all shopping trips and is by far the most important shopping purpose. The leisure activities differentiated by the Microcensus 2005 are listed in Table 3 (Swiss Federal Statistical Office 2007).

Table 3 Activity types for leisure trips in Switzerland according to Microcensus 2005

Activity type	Share of total trips [in %]
Gastronomy visit	21.7
Visit	21.5
Non-sporting outdoor activity	19.6
Active sport	11.9
Cultural event, leisure facility	5.8
Unpaid work	5.4
Home leisure activity	2.4
Church, cemetery	1.8
Return as a recreational activity	1.3
Eating without gastronomy visit	1.2
Companionship as a recreational activity	0.9
Shopping stroll	0.9
Remainder	0.9
Club	0.8
Medicine, wellness	0.6
Trip, vacation	0.6
Passive sport	0.4
Multiple activities	0.4
No answer	1.9
Total	100

Source: Swiss Federal Statistical Office (2007)

The Microcensus 2005 differentiates between 18 leisure activity types. Gastronomy visit, visit, non-sporting outdoor activity and active sport are responsible for already 75% of all leisure trips.

4.1.3 Variability

Variability in microsimulations occurs in three basic contexts and different sources of variability have to be distinguished. Table 4 gives an overview of the different aspects of variability.

Table 4 Aspects of variability in microsimulations

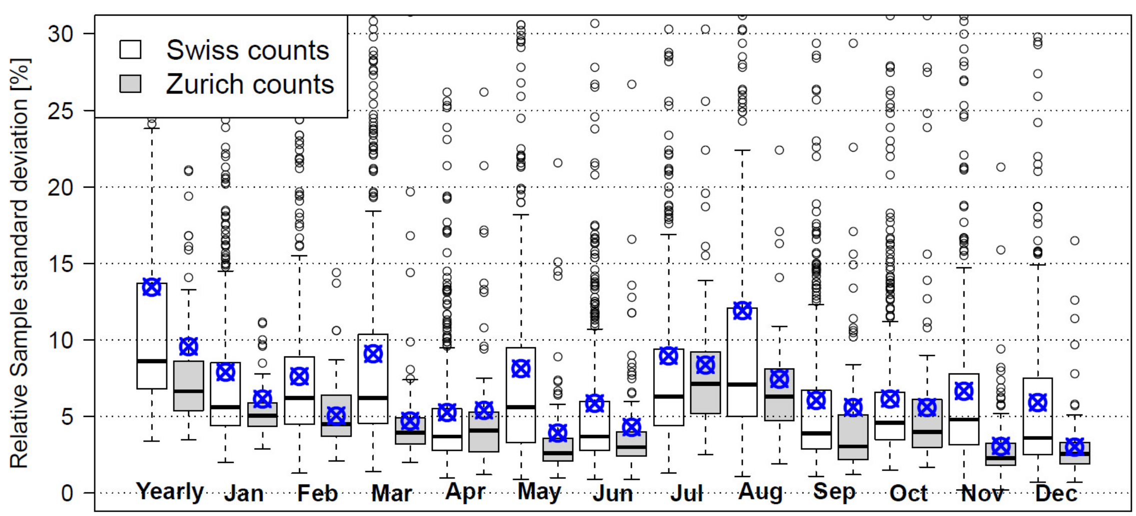
Aspect	Description	Related literature
Random variability		
Inter-run	Stochastic variation between simulation runs with different random number seeds	Wegener (2009); Horni et al. (2011a)
Systematic variability		
Inter-personal	Observed variability in choice making, modelled with explanatory variables	Horni et al. (2011a)
Temporal variability		
Intra-day	Variability of e.g., travel demand within a day	Horni et al. (2011a)
Intra-personal (mid- to long-term)	Seasonal variability caused by general life rhythms	Horni et al. (2011a)

As described in section 3, microsimulations like MATSim try to maximize the score of a certain utility function based on discrete choice theory. Discrete choice models consist of systematic and random parts and model the probability of individuals choosing a given option (Ben-Akiva et al. 1985). The introduction of random parts in the utility function and/or randomness stemming from Monte Carlo realizations with different random number seeds leads to random variability that needs to be accounted for. The destination choice model of MATSim introduced by Horni et al. (2011b) incorporated such a random error term. Until then, the utility function in MATSim was deterministic. Although the co-evolutionary algorithm and the mobility simulation include some randomness (Horni et al. 2011a).

MATSim incorporates systematic variability and temporal variability in terms of intra-day variation. In contrast, temporal variability related to intra-personal variation is missing in MATSim but it is known that mid- to long-term temporal variability is not negligible for travel demand (Schlich et al. 2003; Kitamura et al. 2006).

Out of the three aspects of variability, random variability is an important issue regarding the definition of the level of resolution. The magnitude of fluctuations between simulation runs depends on the aggregation level, i.e. the level of resolution, but also determines which level of detail of e.g., agent interaction processes is observable in the results. Some effects might disappear in the random noise due to the stochastic variation. In order to estimate the magnitude of the stochastic variation of microsimulations the random variation of real traffic volume data can be consulted. In Figure 3, the relative sample standard deviation of daily volumes of Swiss road count data is shown (Horni et al. 2011a).

Figure 3 Relative sample standard deviation of daily volumes of count data



Source: Horni et al. (2011a)

The mean relative sample standard deviation varies over the year between approximately 3% and 10%. The stochastic variation of microsimulations is expected to lie in the same range.

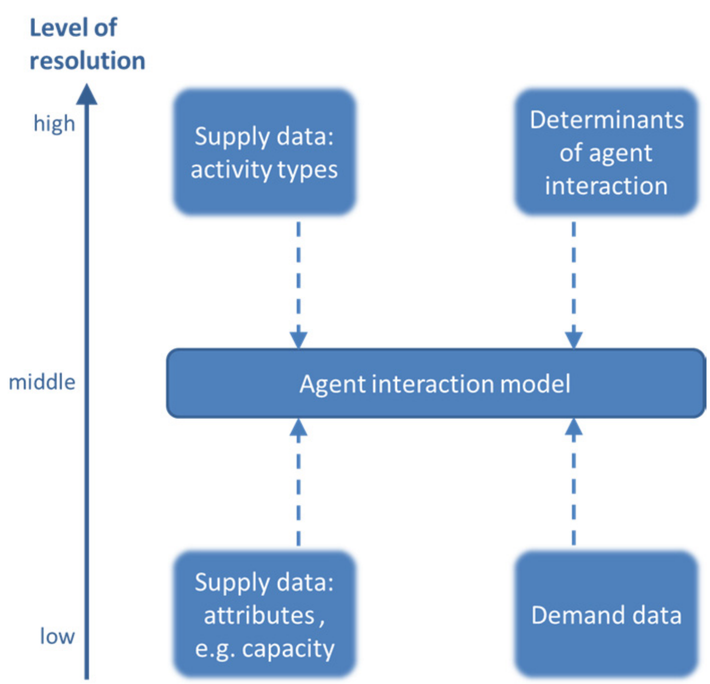
4.1.4 Conclusion

Based on the data analysis, it can be concluded that different data resolutions for supply and demand call for a compromise regarding the different activity types. In addition, assumptions on the capacities of activity infrastructures are necessary. The level of resolution is restricted by demand data and supply data regarding attributes such as capacity.

Furthermore, it is not recommended to account for all identified determinants of agent interaction in the activity infrastructure for several reasons. Firstly, some determinants only have a small influence on agent interaction. Those effects are likely to get lost in the general stochastic variation of microsimulations. Secondly, some determinants such as atmosphere are difficult to define and capture. The uncertainty introduced by possible indicators may exceed the influence and may also get lost in stochastic variation. Thirdly, for some indicators (e.g., constraints and motives) no data can be found. In Switzerland the data availability is comparatively good, but MATSim is designed for applications in the whole world. Therefore, it is important that the data requirements are on a reasonable level. Fourthly, for computational reasons it is advisable to make simplifications and limit the level of resolution.

All in all, a level of resolution is aimed for that lies between the high resolutions of determinants of agent interaction as well as supply data regarding activity types and the low resolutions of demand data and supply data in terms of infrastructure attributes such as capacity. Figure 4 illustrates the middle course that is aimed for.

Figure 4 Targeted level of resolution



4.2 Definition of activity classes

Based on the trade-off described above, the four different activity classes shown in Table 5 are differentiated.

Table 5 Activity classes

Class	Description	Infrastructure examples
Shop retail	Encompasses all retail shopping activities	grocery store
Shop service	Involves shopping activities in repair stores and personal service activities	hairdresser, laundry shop, repair store
Sports & fun	Embraces sport, diversion and relaxation activities	bar, gym, tennis court, golf course
Gastro & culture	Includes dining out and cultural activities	restaurant, canteen, museum, library

Shopping activities are divided into two categories, *shop retail* and *shop service*. This distinction is drawn because different processes are assumed when the crowding level increases. Pan et al. (2011) have shown that customers in a service setting assess crowding differently than in a retail environment because shoppers know that they are in less competition with other customers for products of limited availability. For instance, if the crowding level in a retail store increases, at some point people have to wait a longer time in front of cash registers or to get served by an employee. Whereas in a service shop people tend to have an appointment, in this case it does not matter how many people are present at the shop because an employee has allocated some time for the specific person. Therefore, negative psychological consequences such as stress and discomfort are less present (Pan et al. 2011).

Leisure activities are also separated into two categories, *sports & fun* and *gastro & culture*. The difference between those two classes is that for *sports & fun* activities it is assumed that performing such an activity when only few people are present is more negatively perceived than for *gastro & culture* activities. For *sports & fun* activities a certain level of crowding is beneficial. Holt (1995) observed that the presence of other spectators in baseball games enhanced the overall experience. The work of Eastman et al. (1997) indicated similar effects in public sports viewing bars. Pons et al. (2006) demonstrated that crowding appeared to positively affect the service experience in a discotheque. This relationship is expected to be less present in restaurants and cultural facilities such as museum and libraries. In addition, the assumption is made that the capacity limits for *gastro & culture* infrastructures are sharper. In a theatre or restaurant the capacity is limited by the number of seats whereas in a bar or gym the capacity limit is softer.

In Table 6, the allocation of the activities infrastructure to the four activity classes according to the NOGA commercial types (using NOGA-1995-classification) is shown.

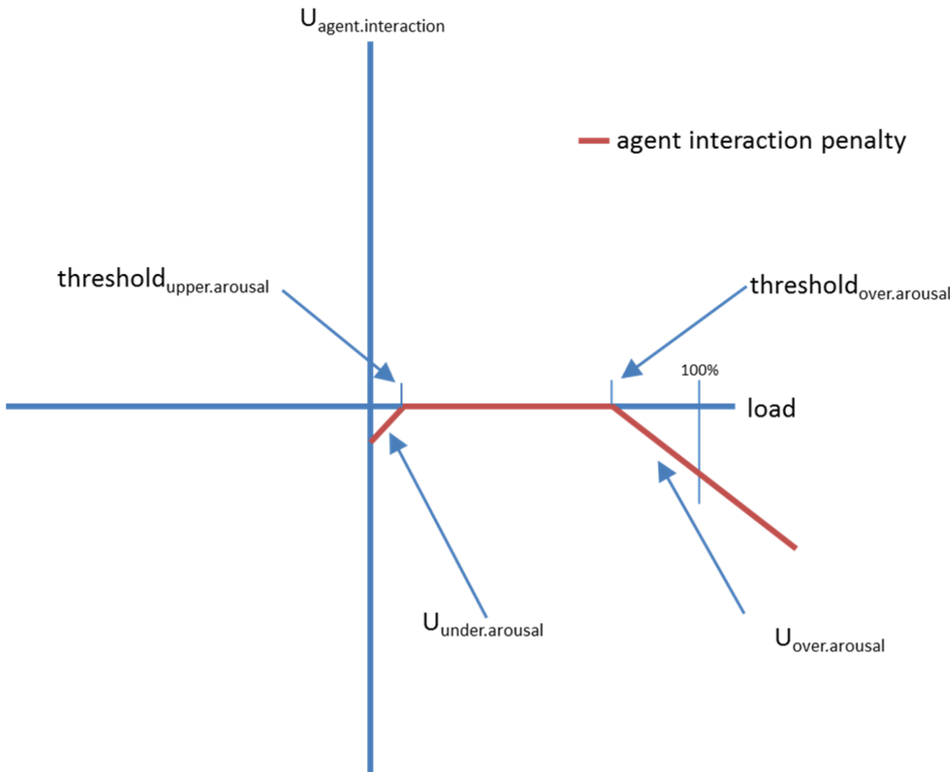
Table 6 Overview of activity classes and NOGA commercial types

Activity class	Subclass	NOGA commercial types
shop retail	*gt2500*	B015211A
	get1000	B015211B
	get400	B015211C
	get100	B015211D
	lt100	B015211E
	other	B015212A-B, B015221A, B015222A, B015223A, B015224A, B015225A, B015226A, B015227A-B, B015231A, B015232A, B015233A-B, B015241A, B015242A-E, B015243A-B, B015244A-C, B015245A-E, B015246A-B, B015247A-C, B015248A-P, B015250A-B
shop service		B015271A, B015272A, B015273A, B015274A, B019301A, B019302A-B, B019305A
sports & fun		B015540A, B019233A, B019234A-C, B019261A, B019262A-B , B019271A, B019272A, B019304A-C
gastro & culture		B015530A, B015551A, B019213A, B019231A-B, B019234D, B019251A, B019252A, B019253A

4.3 Definition of utility-load curves

In modern crowding literature the relationship between utility and load is deemed to have an inverse U shape (Eroglu et al. 2005; Michon et al. 2005). In addition, results of recent studies (e.g., Pan et al. 2011) showed that a medium level of crowding appeared to be optimal. Thus, following the formulation of penalty terms for coming too late or leaving too early, the utility of performing an activity in MATSim is extended by the two penalty terms called $U_{under.arousal}$ and $U_{over.arousal}$. $U_{under.arousal}$ penalises agents performing a shopping or leisure activity in locations with very few visitors and $U_{over.arousal}$ distributes a penalty for highly crowded activity settings. Load is used as a measure for the level of crowding. It is defined as the ratio of the number of agents present at the facility and the maximum number of agents a facility can handle simultaneously (capacity limit). Together the two penalty terms describe an approximation to the inverse U relationship discussed in the literature. Within a certain range ($load_{under.arousal}$-$load_{over.arousal}$) the crowding level is assumed to be optimal and no penalty is computed. Figure 5 shows a schematic overview of the modelled utility-load curve.

Figure 5 General shape of the utility-load curve



$U_{under.arousal}$ and $U_{over.arousal}$ have a form similar to the penalty terms for coming too late or leaving too early. Those penalty terms follow the penalty terms of the Vickrey model of departure time choice and are linear in their time consumption (Charypar et al. 2005).

The agent interaction penalty term $U_{under.arousal}$ is defined as follows:

$$U_{under.arousal}(load, t_{dur}) = \begin{cases} \beta_{under.arousal} * load * t_{dur} & if\ load < load_{under.arousal} \\ 0 & else \end{cases}$$

where,

$$load = 1 - \frac{number\ of\ agents\ present}{capacity},$$

$$load_{under.arousal} = \text{threshold for under-arousal},$$

$$t_{dur} = \text{duration of activity, and}$$

$$\beta_{under.arousal} = \text{marginal utility of under-arousal}$$

The penalty term $U_{over.arousal}$ is defined in a similar way:

$$U_{over.arousal}(load, t_{dur}) = \begin{cases} \beta_{over.arousal} * load * t_{dur} & if\ load > load_{over.arousal} \\ 0 & else \end{cases}$$

where,

$$load = \frac{number\ of\ agents\ present}{capacity},$$

$$load_{over.arousal} = \text{threshold for over-arousal,}$$

$$t_{dur} = \text{duration of activity, and}$$

$$\beta_{over.arousal} = \text{marginal utility of over-arousal}$$

$U_{over.arousal}$ and $U_{under.arousal}$ are load- and time-dependent. In order to capture agent interaction dynamics with constantly changing infrastructure occupancies, load is updated every 15 minutes. For each activity class different thresholds and marginal utilities are selected. Thus, their specific utility-load relationship can be accurately modelled. For marginal utilities, the typical Vickrey scenario values of -6€/h, -12€/h, and -18€/h (see Charypar et al. 2005) according to the magnitude of influence are used for a first implementation. Table 7 gives an overview of the tentative parameters employed for each activity class.

Table 7 Tentative parameters for activity classes

Parameter	*shop retail*	*shop service*	*sports & fun*	*gastro & culture*
$load_{under.arousal}$	0.1	0.1	0.2	0.1
$load_{over.arousal}$	0.75	0.9	1.0	0.9
$\beta_{under.arousal}$	-12 €/h	-12 €/h	-12 €/h	-12 €/h
$\beta_{over.arousal}$	-12 €/h	-6 €/h	-18 €/h	-12 €/h

For *shop retail* activities it is assumed that utility decreases well before the capacity limit is reached. For instance, people have to wait gradually longer in front of cash registers when the crowding level increases. Therefore, an upper load threshold of 0.75 is selected. The penalty for under-arousal is evaluated for loads up to 0.1. The marginal utilities are assumed to lie in the middle range. As explained in section 4.2, *shop service* activities are less sensitive to higher loads. Therefore, the upper load threshold is set to 0.9 and the marginal utility for over-arousal has a value of -6 €/h. The class *sports & fun* combines activities where the presence of other people increases the utility of performing an activity. Hence a penalty is applied for loads up to 0.2 and the penalty for over-arousal is computed not until the capacity limit is reached. For *gastro & culture* activities a less positive effect of the presence of other people is assumed. The penalties for under- and over-arousal are computed for loads up to 0.1 and loads exceeding 0.9, respectively.

4.4 Definition of capacities

Capacities of shopping and leisure infrastructures have to be specified based on assumptions as there are no such data available. Capacity is defined as the maximum number of people that an activity location can momentarily cope with. It is important to note that capacity represents the point where people are no longer able to reasonably perform their activities in a given location. This limit might be reached well before the physical carrying capacity of a location. For example in restaurant, capacity is reached when all seats are taken, even if there is still space for more people to enter the restaurant.

Basically the two different approaches shown in Table 8 are used to specify the capacity.

Table 8 Approaches for capacity specification

Approach	Description	Application
Area	Capacity is deduced based on the given sales area	Retail stores
Number of employees	Capacity is defined assuming the number of people an employee can handle	Service shops, bar, discotheque, dancing, night club, arcade, casino, dancing school, sport clubs, operation of sport facilities, sauna, solarium, amusement parks, restaurant, libraries, museum, zoo, gardens, natural parks, etc.

4.4.1 Capacity definition based on sales area

The area approach is applied for retail stores. The Federal Enterprise Census 2001 Sectors 2 and 3 (Swiss Federal Statistical Office 2001) differentiates the following retail store sales area categories:

- Consumer markets with a sales area >2‘500m^2
- Superstores within a sales area range of 1’000-2’499m^2

- Supermarkets within a sales area range of 400-999m^2
- Big stores within a sales area range of 100-399m^2
- Small stores with a sales area <100m^2

Capacity is estimated without taking the number of employees into account because it is assumed that the sales area is a more accurate capacity indicator than the number of employees. In a retail store a customer is less dependent on the service of a sales person; he can stay at the shop and look for purchases without being served. Not until the customer needs a question to be answered or starts to check out he occupies an employee. When the crowding level increases, the number of cashiers is indeed a limiting factor, but this parameter is unknown and there is a lot of uncertainty involved when estimating the number of cashiers based on the number of employees. This parameter may vary strongly from store to store. Therefore, the sales area is used for estimating the capacity. The effect of longer waiting periods in front cash registers as the load increases, is represented by a $load_{over.arousal}$ of 0.75 as detailed in section 4.3.

The area which is accessible for customers is set to 50% of the total sales area which includes area for shelves, cash registers etc. A density of 0.135 Person/m^2 is taken as the density limit. This corresponds to 10% of the pedestrian traffic density of LOS E (Forschungsgesellschaft für Strassen- und Verkehrswesen 2001). LOS E is defined as the state where the capacity limit for pedestrians is reached. It is assumed that the capacity limit in shops is reached ten-times earlier. The formula for computing the capacity for retail stores is as follows:

$$capacity = f_{substract} * density_{limit} * random(r_{sales\ area})$$

where,

$$f_{substract} = 0.5,$$

$$density_{limit} = 0.135\ {}^{P}/_{m^2}, \text{ and}$$

$$random(r_{sales\ area}) = \text{random pick in the sales area range given by NOGA category}$$

A random pick in the sales area range is performed. For consumer markets the highest sales area is set to 7'000m^2 (GfK Switzerland AG 2011). For small stores the capacity is assumed to account for 10. For other non-grocery retail stores the sales area is not given. Nevertheless, the area approach is applied for capacity estimation in order to be consistent with the capacity definition of all other retail stores. Based on sector data (GfK Switzerland AG 2011), the assumption is made that the sales area lies in the range of 150-1'000m². Table 9 shows the defined capacities for *shop retail* stores.

Table 9 Capacities for *shop retail* stores

Category [-]	Sales area [m^2]	Capacity [Number of customers]
Shop retail gt2500	>2'500	169-473
Shop retail get1000	1'000-2'500	67-169
Shop retail get400	400-999	27-67
Shop retail get100	100-399	10-27
Shop retail lt100	<100	10
Shop retail other	150-1'000	10-67

All in all *shop retail* capacity can vary between 10 and 473 customers.

4.4.2 Capacity definition based on number of employees

For *shop service* and leisure infrastructures capacity is specified based on the number of employees derived from the Federal Enterprise Census 2001 Sectors 2 and 3 (Swiss Federal Statistical Office 2001). The number of employees is given in the form of full-time-equivalents. In order to estimate the capacity the following formula is applied:

$$capacity = (1 - f_{vacancy} - f_{shift\ operation}) * FTE * random(r_{cap\ employee})$$

where,

$$f_{vacancy} = 0.15,$$

$$f_{shift\ operation} = 0.15,$$

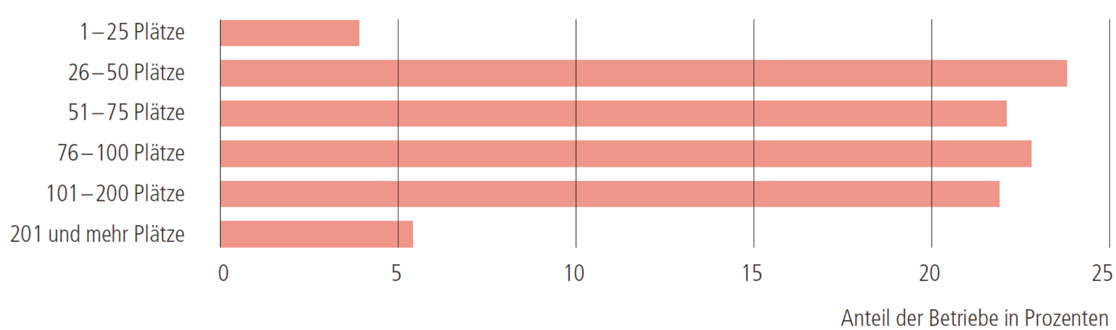
$$FTE = \text{full time equivalent, and}$$

$$random(r_{cap\ employee}) = \text{random pick in the capacity range of an employee}$$

Capacity of a single employee is defined as the number of customers an employee can serve simultaneously. For 12 groups of commercial types a certain capacity range of a single employee is estimated. Out of this range a random pick is performed and multiplied with the full-time-equivalent. Then the capacity is reduced in order to account for vacancies and shift operation. It is assumed that 15% of the full-time-equivalent has to be subtracted for shift operation. According to the Swiss statistics on volume of work of 2010 the average absence rate accounts for 3.8% (Swiss Federal Statistical Office 2010a). This percentage excludes absences for vacation and holidays. Under the assumption of 5 vacation weeks per year, the vacancy factor is rounded up to 15%. In summary, full-time-equivalents are reduced by 30%.

The data research on capacity ranges of an employee ($r_{cap\ employee}$) showed that there is very sparse information. Capacity data could only be retrieved for certain infrastructures on an enterprise level and not on an employee level. For those, inferences on the capacity range of a single employee were drawn. For instance, Gastrosuisse provides the distribution of the number of seats of restaurants in Switzerland which is illustrated in Figure 6.

Figure 6 Distribution of the number of seats of restaurants in Switzerland



Source: GastroSuisse (2011)

Taking the range of number of employees derived from the Federal Enterprise Census 2001 Sectors 2 and 3 into account, one can estimate the capacity of a single employee. This procedure was applied for the following groups of commercial types:

- Restaurants and canteens based on GastroSuisse (2011)
- Theatre, orchestra, circus, museum, etc. based on Schweizerischer Bühnenverband (2011)
- Cinema based on Swiss Federal Statistical Office (2011b)
- Operation of sport facilities based on A & M Baud-Bovy (1998)

For all other groups capacity ranges were arbitrarily set. Table 10 shows the specified capacity ranges of a single employee for different commercial types. In some cases, estimating the capacity based on the number of employees lead to implausibly low or high capacities since the capacity apparently does not increase linear with the number of employees. For those groups a base capacity is defined as a starting point from which capacity increases with the number of employees. For sport facilities such as stadiums the capacity is set to rise exponentially with increasing number of employees since the relationship between capacity and number of employees is assumed to be exponential.

Table 10 Capacity range of a single employee for different commercial types

Group of commercial types [-]	NOGA numbers [-]	Capacity range per employee [Number of customers]	Base capacity [Number of customers]
shop service	B015271A, B015272A, B015273A, B015274A, B019301A, B019302A-B, B019305A	1	0
bar, discotheque, dancing's, arcades, casino, etc.	B015540A, B019234B-C, B019271A	10-20	0
dancing school, tennis school, golf schools, etc.	B019234A, B019262B, B019272A	20-30	0
operation of sport facilities	B019261A	1-170	30
sport club	B019262A	1-2	20
sauna, solarium, gym, thermal bath, etc.	B019304A-C	2-10	0
amusement park	B019233A	1-25	100
restaurant, canteen	B015530A, B015551A	10-20	0
cinema	B019213A	1-8	0
theatre, orchestra, circus, museum, etc.	B019231A-B, B019234D, B019252A	1-8	50
library	B019251A	1-5	20
zoo, natural parks, etc.	B019253A	1-15	50

In order to exclude implausibly high capacities, an upper limit of 1'000 is set for restaurants and canteens. The same applies for cinemas where the capacity is restricted to 800.

5 Implementation and application

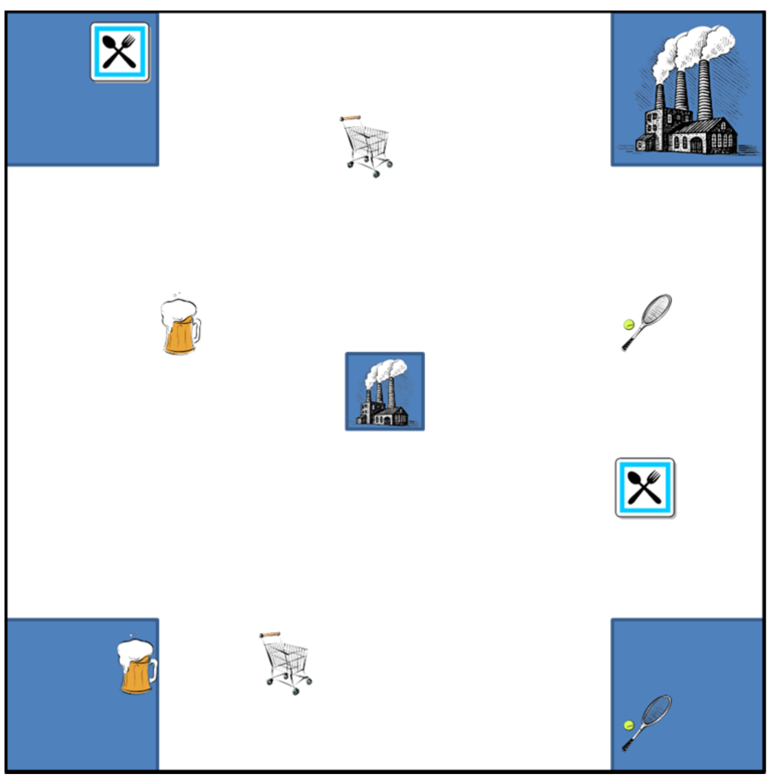
The whole model is first tested in a synthetic small-scale scenario and then applied to a real-world scenario. The synthetic small-scale scenario is used to vary the parameters of the agent interaction model and analyse the effects and implications associated with it. The real-world scenario provides the basis for validating the model.

5.1 Synthetic small-scale scenario

5.1.1 Build-up

A grid with 1'600 squares and a side length of 10 km is used as a network. It consists of 6'560 links and 1'681 nodes. The link capacity is set to 600 vehicles per hour. Figure 7 gives an overview of the scenario.

Figure 7 Overview of the synthetic small-scale scenario



In each corner of the grid a zone of 4 km^2 is defined. In the centre, a fifth zone of 1 km^2 is added. The population consists of 3'000 agents whose home locations are equally distributed over the five zones. Work facilities are concentrated in the centre and top-right zones. Shopping and leisure facilities are randomly distributed over the study area. Table 11 summarises the available shopping and leisure facilities.

Table 11 Shopping and leisure facilities in the synthetic small-scale scenario

Category	Number of facilities [-]	Capacity range [Number of customers]	Opening times [hh:mm-hh:mm]
shop retail	3	61-201	07:30-19:00
shop service	4	8-29	08:00-19:00
sports & fun	14	3-43	09:00-24:00
gastro & culture	13	9-62	09:00-24:00

Each agent's daily plan contains a work activity in the centre or top-right zone. Shopping and leisure activities are enclosed according to arbitrarily set probabilities. This leads to the demand for shopping and leisure activities presented in Table 12. Desired activity durations are arbitrarily set to the values listed in Table 12.

Table 12 Demand for discretionary activities in the synthetic small-scale scenario

Category	Number of trips [-]	Share of total number of activities [%] (without home)	Desired activity duration [h]
shop retail	1'190	19.2	0.5
shop service	159	2.5	1.0
sports & fun	912	14.8	1.0
gastro & culture	918	14.8	2.0

5.1.2 Calibration

In order to calibrate the scenario, test runs with the Charypar-Nagel scoring function were carried out. For more information on the Charypar-Nagel scoring function and its related scoring parameters please refer to Charypar et al. (2005). Results showed that agents tended to perform very short shopping activities after the opening hours. This pattern might be plausible for initial plans, but agents should learn and remove those plans from their memory through the evolution process. Analysis of these plans revealed that agents do not have too many activities that need to be squeezed into the day. Therefore, changes of the demand could not resolve the problem. But since the marginal utility of waiting in the Charypar-Nagel scoring function is 0 (agents are only penalized through loosing time to perform an activity) agents very slowly rescheduled their shopping activity during the iterations. After 500 iterations the problem still remained. It is possible that some agents preferred (too) late shopping trips to avoid being stuck in traffic during rush hour, but increasing the link capacity did not solve the issue. Therefore, the marginal utility of waiting was set higher. In this context, it was also necessary to define a higher marginal utility of leaving early because otherwise, agents only shortened their shopping activity duration when the shop was closed. The employed scoring parameters are listed in Table 13.

Table 13 Overview of scoring parameters

Parameter	Charypar Nagel value [€/h]	Adapted Value [€/h]
Marginal utility of any activity	6	6
Marginal utility of travel time	-6	-6
Marginal utility of waiting	0	-150
Marginal utility of coming late	-18	-18
Marginal utility of leaving early	-18	-150

Source: Charypar et al. (2005)

Test runs with the adapted values yielded more plausible results, but a small amount of people still tried to perform a shopping activity after the opening hours.

5.1.3 Configurations

The small-scale scenario is run with the following configurations:

Configuration 0

In this case, a run with the Charypar-Nagel scoring function (Charypar et al. 2005) and the adapted scoring parameters detailed in Table 13 is performed. Thus, no agent interaction penalties are given. Agents can store up to 4 plans in their memory. Time and route are the available choice dimensions during the iterations.

Configuration 1

The scenario is run with the agent interaction model. Destination choice is not permitted. Three different parameter sets are tested within this configuration. Table 14 shows the tested parameter sets of configuration 1.

Table 14 Tested parameter sets of configuration 1

Parameter	*shop retail*	*shop service*	*sports & fun*	*gastro & culture*
Configuration 1a				
$\beta_{under.arousal}$	-12 €/h	-12 €/h	-12 €/h	-12 €/h
$\beta_{over.arousal}$	-12 €/h	-6 €/h	-18 €/h	-12 €/h
Capacity range	61-201 p	8-29 p	3-43 p	9-62 p
Configuration 1b				
$\beta_{under.arousal}$	-1.2 €/h	-1.2 €/h	-1.2 €/h	-1.2 €/h
$\beta_{over.arousal}$	-1.2 €/h	-0.6 €/h	-1.8 €/h	-1.2 €/h
Capacity range	61-201 p	8-29 p	3-43 p	9-62 p
Configuration 1c				
$\beta_{under.arousal}$	-1.2 €/h	-1.2 €/h	-1.2 €/h	-1.2 €/h
$\beta_{over.arousal}$	-1.2 €/h	-0.6 €/h	-1.8 €/h	-1.2 €/h
Capacity range	122-401 p	16-58 p	6-86 p	18-124 p

While the capacity ranges are held constant for configuration 1a and 1b, capacities are doubled for configuration 1c.

All four parameter sets use the initially assumed thresholds for over- and under-arousal displayed in Table 7. Configuration 1a also uses the tentative marginal utilities listed in this table. For configuration 1b and 1c, the marginal utilities are ten-times lower than in configuration 1a.

Configuration 2

The scenario is run with the agent interaction model and the same parameter set as with configuration 1b. Destination choice is added as a choice dimension during the iterations.

In Table 15, an overview of the employed configurations in the synthetic small-scale scenario is given.

Table 15 Overview of configurations in the synthetic small-scale scenario

Aspect	Configuration 0	Configuration 1a-c	Configuration 2
Number of plans in memory	4	4	4
Time choice	✓	✓	✓
Route choice	✓	✓	✓
Destination choice	×	×	✓
Agent interaction	×	✓	✓

5.2 Real-world scenario

As a real-world scenario, the 10%-Zurich scenario is adapted; a widely used and well calibrated setting for testing developments within the framework of MATSim. It served as a real-world example in many projects (Balmer et al. 2009; Horni et al. 2011b). Therefore, an adjusted version will be used for validation.

The population is derived from the Swiss Census of Population 2000 (Swiss Federal Statistical Office 2010b). Travel demand is generated based on the National Travel Survey for the years 2000 and 2005 (Swiss Federal Statistical Office 2007). Out of this demand that covers whole Switzerland, a cut-out is taken within circle with radius 30km around a central place in Zurich (Bellevue) and only people performing at least one activity in that circle are taken into account. Then a 10% sample of car traffic in this area is drawn, resulting in more than 66'000 agents and corresponding plans. The basic version of the 10% Zurich scenario differentiates between 5 activity types: home, work, education, leisure, and shop. In order to test the agent interaction model, shop activities have to be divided into *shop retail* and *shop service* activities and leisure activities have to be partitioned into *sports & fun* and *gastro & culture* activities. Based on the Swiss Federal Statistical Office (2007), the following demand distributions are applied. For shop demand it is assumed that every 20th trip is a *shop service* activity. Leisure activities are equally distributed into *sports & fun* and *gastro & culture* activities. This leads to the demand listed in Table 16.

Table 16 Travel demand in the 10% Zurich scenario

Category	Number of trips [-]	Share of total number of activities [%]
home	137'588	48.8
work	68'937	24.4
education	5'694	2.0
shop retail	25'612	9.0
shop service	1'378	0.5
sports & fun	21'398	7.6
gastro & culture	21'469	7.6

The road network described in Balmer et al. (2009) is used. It consists of 24’185 nodes and 60’518 links.

Home locations are derived from the Swiss Census of Population 2000 (Swiss Federal Statistical Office 2010b). More than 1.3 million home locations are included in the data set for Switzerland. All other facilities for work, education, shop, and leisure activities are computed from the Federal Enterprise Census 2001 (Swiss Federal Statistical Office 2001). A couple of adjustments and refinements were made to the work and the discretionary activities facilities data set generated by Meister (2008). For discretionary activity locations, enterprises from the Federal Enterprise Census 2001 were assigned to the four newly defined activity classes *shop retail*, *shop service*, *sports & fun*, and *gastro & culture* according to Table 6. In addition, opening times for shopping and leisure facilities were refined. Table 17 details the newly specified opening times.

Table 17 Opening times for shopping and leisure facilities

Category	Opening times [day-day, hh:mm-hh:mm]
shop retail	According to the next retail store from sample data set containing opening hours and address of Migros, Coop, Denner, and Pick Pay
shop service	Monday-Friday, 08:00-18:00
sport facilities	Monday-Friday, 09:00-22:00, Saturday-Sunday, 09:00-20:00
bar, discotheque, casino	Monday-Friday, 09:00-24:00, Saturday-Sunday, 16:00-24:00
restaurant, natural parks	Monday-Sunday, 09:00-24:00
theatre, cinema, orchestra	Monday-Sunday, 14:00-24:00
libraries, file rooms	Monday-Friday, 08:00-18:00, Saturday, 09:00-16:00
zoo, amusement park	Monday-Sunday, 09:00-18:00
museum	Tuesday-Saturday, 10:00-18:00, Sunday, 10:00-16:00

Capacities were defined following the approaches explained in section 4.4.

For the validation, count data of the Federal Roads Office and the city of Zurich of the year 2005 and 2004, respectively, as detailed in Balmer et al. (2009) are used. There are 159 count stations within the 30 km circle around Bellevue. In order to reduce boundary effects, only 123 stations located in a 12 km circle around Bellevue are taken into account. Hourly average values for a workday are employed for comparison. They are computed by taking the average of the measured volumes from Tuesday to Thursday. Public holidays and the 5% highest deviations are excluded.

5.2.1 Configurations

The 10%-Zurich scenario is run with the following configurations:

Configuration 0

In this case, a run with the Charypar-Nagel scoring function (Charypar et al. 2005) and the Charypar-Nagel scoring parameters detailed in Table 13 is performed. Thus, no agent interaction penalties are given. Agents can store up to 4 plans in their memory. Time and route are the available choice dimensions during the iterations.

Configuration 1

The scenario is run with the agent interaction model where the agent interaction parameters displayed in Table 18 are used.

Table 18 Agent interaction parameters of configuration 1

Parameter	*shop retail*	*shop service*	*sports & fun*	*gastro & culture*
$load_{under.arousal}$	0.1	0.1	0.2	0.1
$load_{over.arousal}$	0.75	0.9	1.0	0.9
$\beta_{under.arousal}$	-1.2 €/h	-1.2 €/h	-1.2 €/h	-1.2 €/h
$\beta_{over.arousal}$	-1.2 €/h	-0.6 €/h	-1.8 €/h	-1.2 €/h

Time and route are the available choice dimensions during the iterations. Destination choice is not permitted.

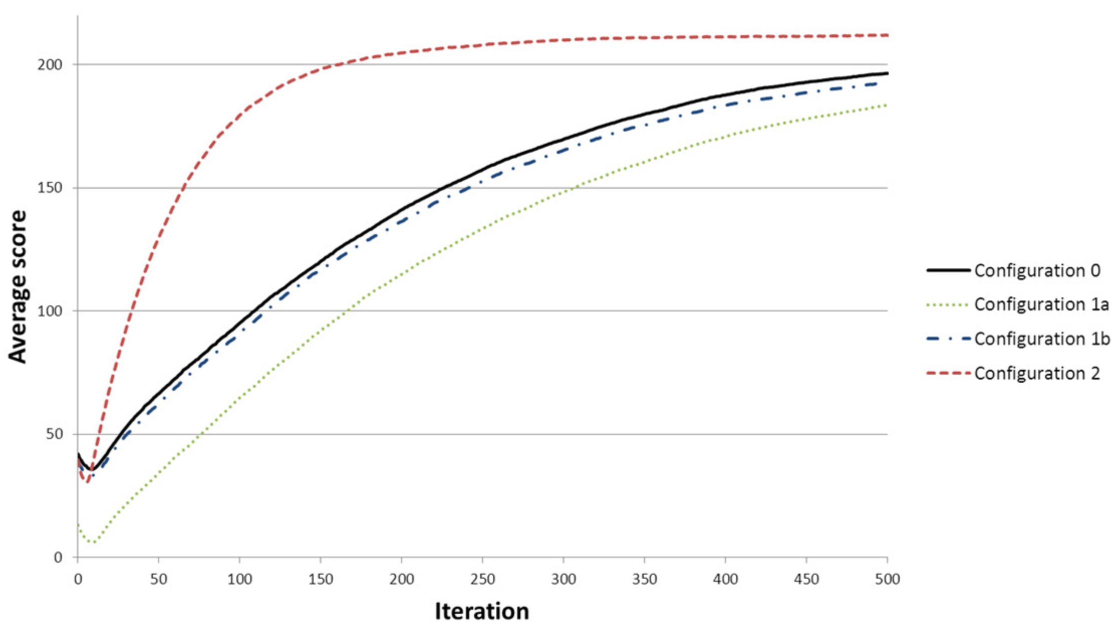
6 Results and discussion

First calibration results of runs with different agent interaction model settings in the synthetic small-scale scenario are discussed. Thereupon, validation results of the real-world scenario are analysed.

6.1 Synthetic small-scale scenario

In Figure 8, the development of the average score during the iterations with different configurations is shown.

Figure 8 Development of average score during the iterations



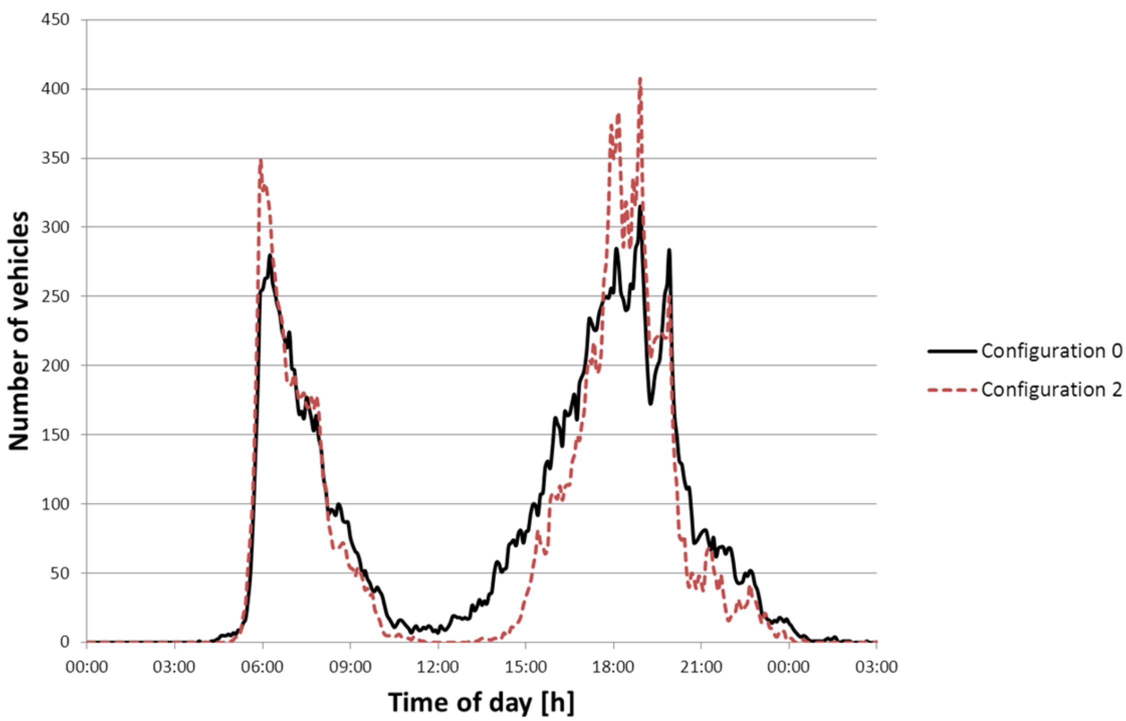
The average score curve of all configurations is characterized by an initial decrease until iteration 5-8. This can be explained by the optimisation process and the given time window for the starting of a work activity, as mentioned in Balmer et al. (2007). Probably a lot of agents simultaneously try out similar plans, resulting in high traffic volumes on preferred roads and consequently high travel disutilities (and corresponding low scores).

The progressions of the average score with configuration 0, 1a, and 1b are very similar since agents have the same choice dimensions (time and route) available. The average score for configuration 1a is smaller than for configuration 1b due to the ten-time higher marginal utilities of the agent interaction penalties.

A different average score-developing is observed with configuration 2 where agents can perform destination choice for discretionary activities. After an initial decrease, the average score starts to ascend rapidly. The system relaxes faster with configuration 2 since the destination choice module in MATSim applies a probabilistic best response approach instead of varying the destination randomly (see section 2.2.1). Furthermore, a higher average score is reached because agents have an additional degree of freedom (destination choice for discretionary activities).

Figure 9 illustrates the flow in the system during the course of the day after 500 iterations with configuration 0 and 2. Configuration 1a, 1b, and 1c are not shown for more clarity because the flow of those configurations is very similar to configuration 0 since agents have the same choice dimensions during the iterations. The only difference between the four is the agent interaction set-up. Since destination choice is not permitted, the resulting flow changes of agent interaction are small.

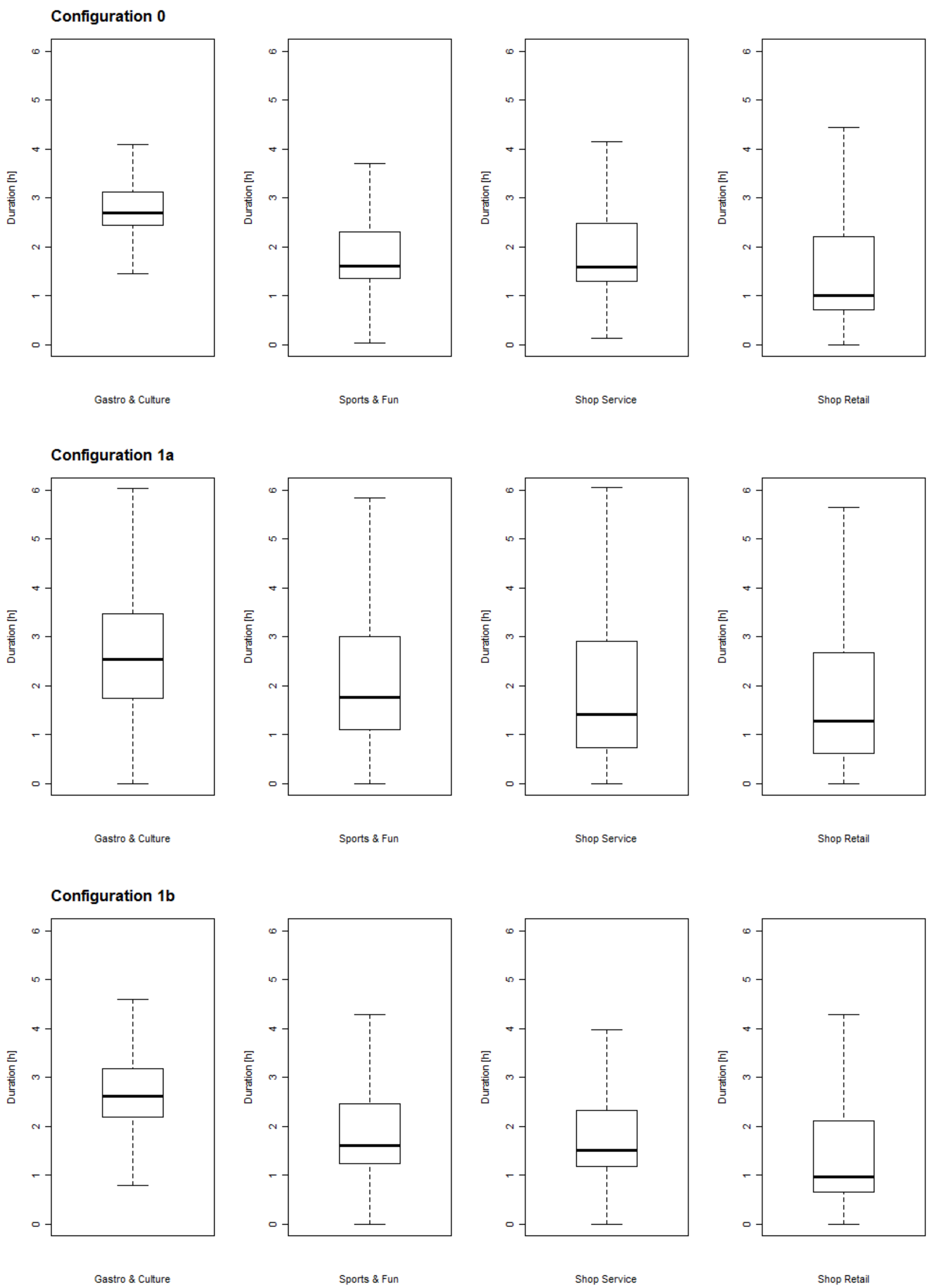
Figure 9 Flow in the system during the course of the day after 500 iterations



Both flows are characterised by sharp peak in the morning and a second broader peak in the evening. The morning-peak is lower and actually smaller than the evening-peak. This is plausible since the evening-peak is higher in reality (Swiss Federal Statistical Office 2007). The strong decline in between shown in Figure 9 cannot be observed in reality. This is due to the fact, that in the synthetic small-scale scenario travel demand is simplified and does not reflect real travel demand. For instance, agents simply go to work with a desired duration of 8 hours and e.g., lunch breaks are not simulated.

In Figure 10, boxplots of the activity durations after 500 iterations are plotted.

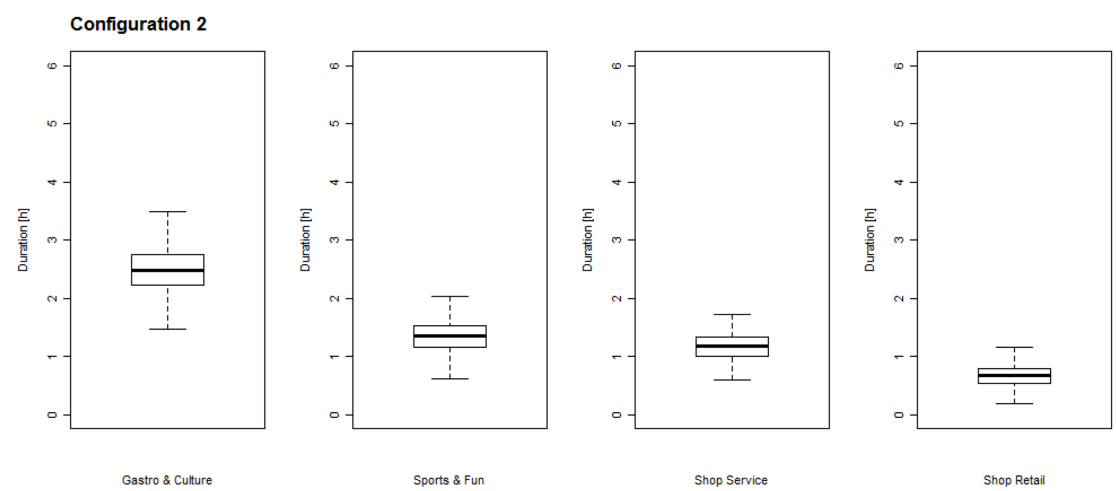
Figure 10 Boxplots of activity durations after 500 iterations



Durations of discretionary activities with configuration 0 and 1b are very similar. With configuration 1b, the median durations of each activity classes are slightly reduced by a maximum of 5%. In contrast, durations with configuration 1a are more widely distributed and more variation between the durations is observed. The median durations increase for *sports & fun* and *shop retail* activities and decrease for *gastro & culture* and *shop service* activities. It is assumed that the high agent interaction penalties within configuration 1a dominate the score composition and therefore other parts of the scoring function (e.g., desired activity durations) are less taken into account by the agents during the iterations which leads to the high activity duration differences in comparison to configuration 0 and 1b.

Figure 11 shows the boxplot of activity durations after 500 iterations for configuration 2.

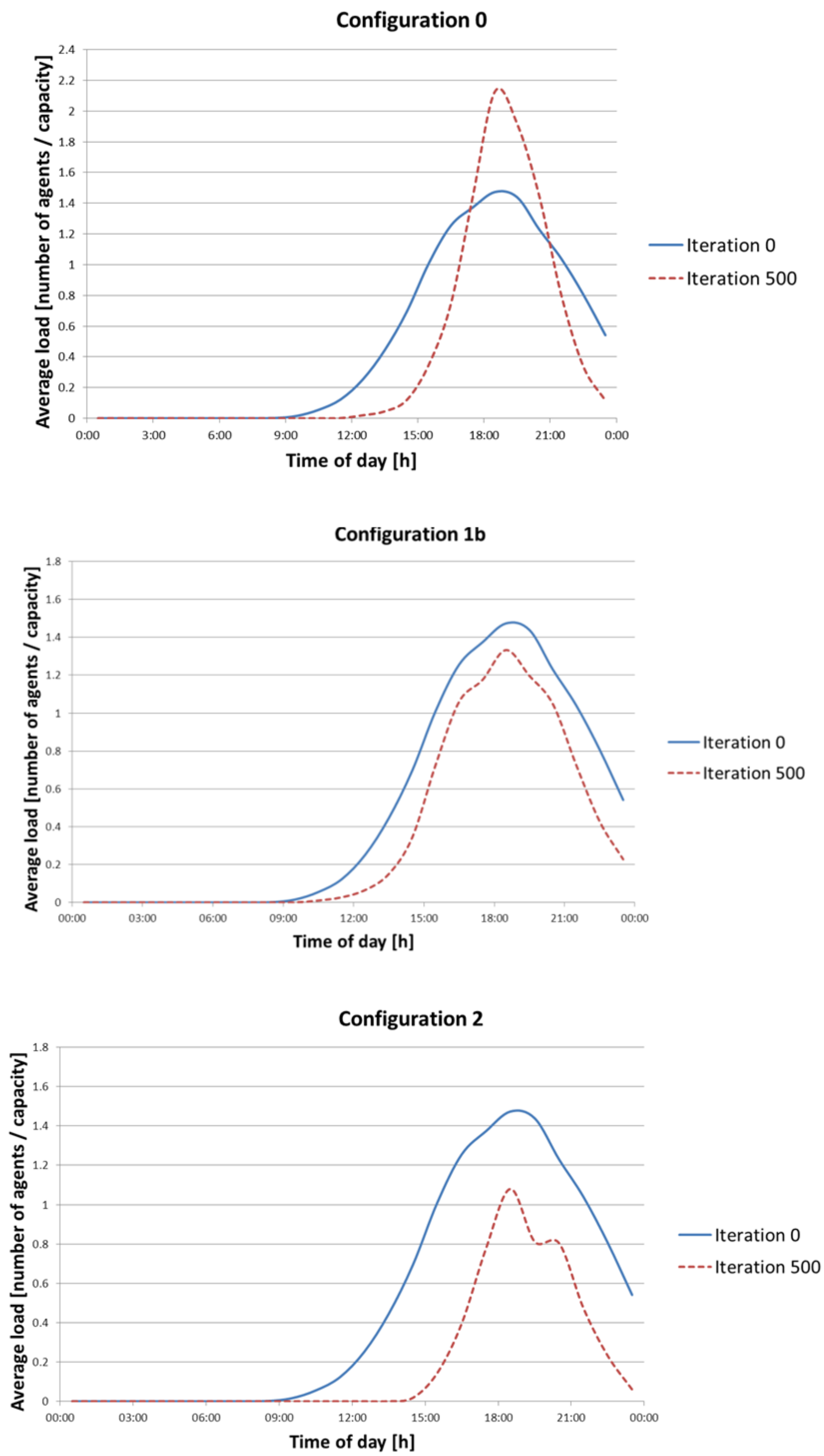
Figure 11 Boxplots of activity durations after 500 iterations for configuration 2



Discretionary activity durations with configuration 2 are considerably more narrowly distributed than with configuration 0 and 1 (see Figure 10). More importantly, agents spend less time for discretionary activities with configuration 2. The median durations decrease up to 34% in comparison to configuration 0.

In Figure 12, the average load of all discretionary activity facilities for iteration 0 and 500 with different configurations is shown.

Figure 12 Development of average load of discretionary activity facilities



The average load curve of the initial demand of all configurations (iteration 0) starts to increase at 09:00 o'clock. Obviously, there are agents who work for a very short period and then perform their discretionary activity already in the morning. These agents get a lower score since the desired activity duration for work is 8 hours. Therefore the average load curve with all three configurations starts to increase later after the optimization process has been employed (iteration 500).

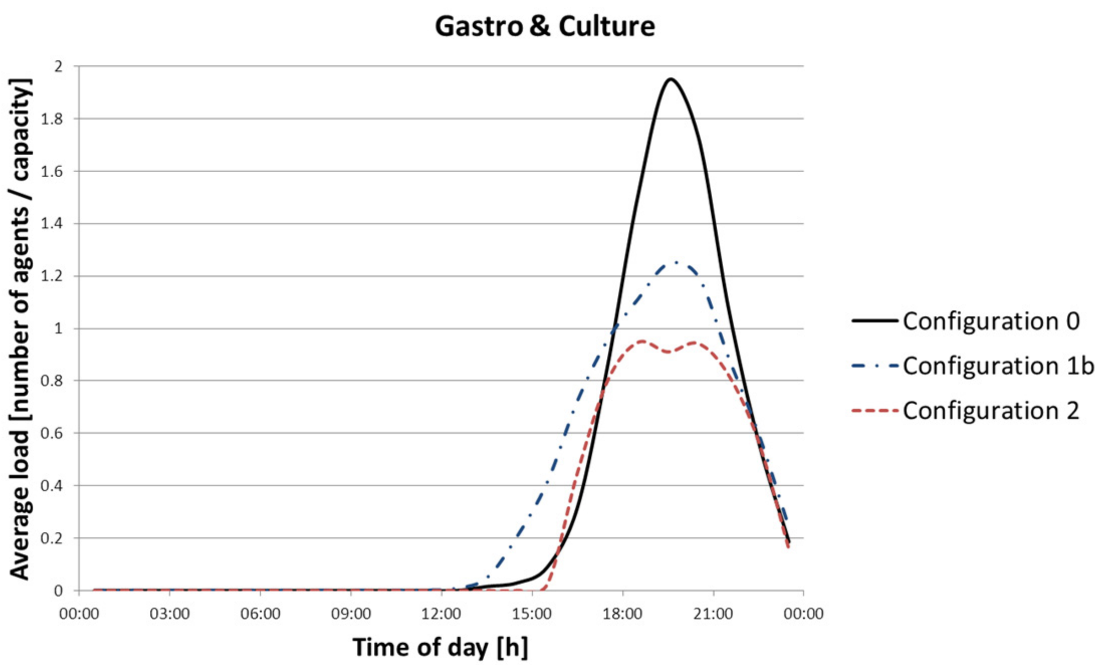
With configuration 0, a high peak at 18:30 o'clock is observed. This peak gets sharper and even higher during the iterations since overloaded facilities have no effect on agent's score. After 500 iterations, all facilities are overloaded in average from 17:30 until 21:30 o'clock. During this time span the capacity of over 30% of the facilities is exceeded, in some cases the load amounts to over 13.

The average load peak after 500 iterations at 18:30 o'clock still exists with configuration 1b, but is substantially smaller. The number of over- and under-loaded facilities is reduced since agents reschedule their shopping or leisure activity in order to avoid an agent interaction penalty. Nevertheless, still over 30% of the facilities are overloaded from 18:30 until 20:30 o'clock. The maximum observable load is reduced to 6.

The number of overloaded facilities during this time span after 500 iterations accounts for around 20% with configuration 2 where agents can also change the discretionary activity location. The peak is also reached at 18:30 o'clock. The maximum observable load decreases to 3.6. Shopping and leisure facilities start being occupied not until 12:30 o'clock. Until 14:30 o'clock very few agents perform a discretionary activity. With configuration 0 and 1b, agents execute a shopping or leisure activity already earlier.

A closer look at the occupancies of *gastro & culture* facilities is presented in Figure 13.

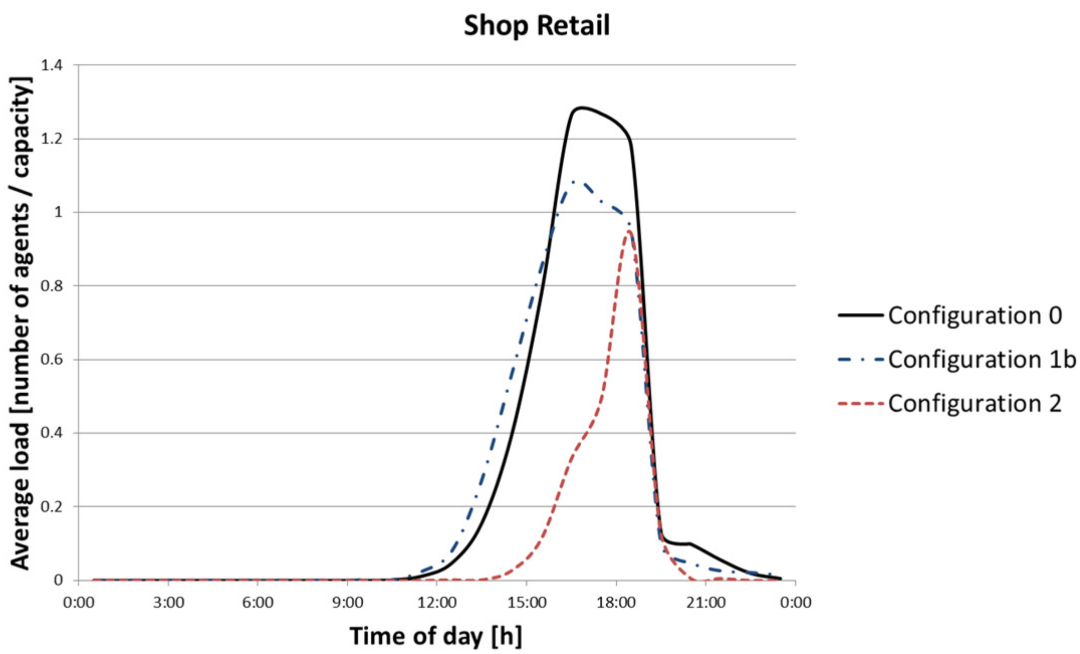
Figure 13 Average load of *gastro & culture* facilities after 500 iterations



With configuration 1b, the load curve has a considerably smaller peak in comparison to configuration 0. The load curve for configuration 2 is narrower but the peak is wider and lasts from 18:30 until 20:30 o'clock. With the destination choice available as choice dimension, agents are able to choose a location with an optimal level of crowding at the optimal point in their daily activity chain since rescheduling the activity chain is not the only way to avoid an agent interaction penalty. Thus, the timeframes for performing a *gastro & culture* activity with configuration 2 gets smaller with a simultaneously more beneficial level of crowding.

Figure 14 illustrates the average load of *shop retail* facilities after 500 iterations with different configurations.

Figure 14 Average load of *shop retail* facilities after 500 iterations

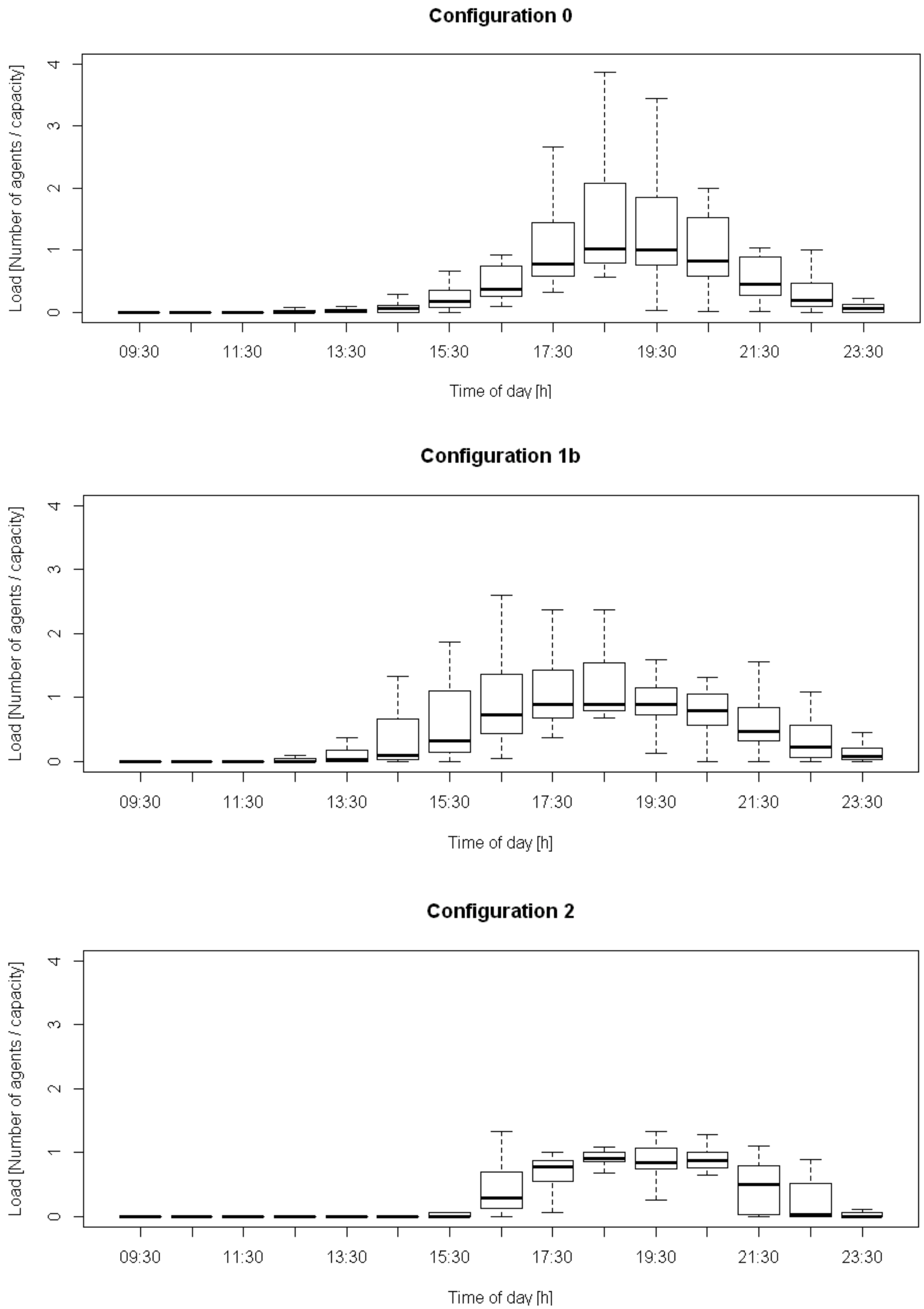


Regardless of the configuration, it can be seen that the average load of shopping facilities decreases strongly after 19:00 o'clock when they close. However, the effect of agents staying at the shopping facilities after the opening times for a very short time span is still observable, especially for configuration 0 and 1b.

There is a sharp peak observable with configuration 0. Adding the agent interaction model to the scoring function without allowing destination choice (configuration 1b) does reduce the height of the peak. In addition, the load curve is widened. Agents reschedule their retail shopping trips in order to perform the shopping activity without being penalised through an agent interaction penalty. The maximum load for the most occupied *shop retail* facility with configuration 1b is decreased by 20%. Nevertheless, the peak only reduces slightly since the load for all other shopping stores is higher. With configuration 2, the load curve gets narrower again, very similar to the pattern observed for *gastro & culture* facilities in Figure 13.

Figure 15 shows selected boxplots of the load of discretionary activity facilities during the course of the day after 500 iterations.

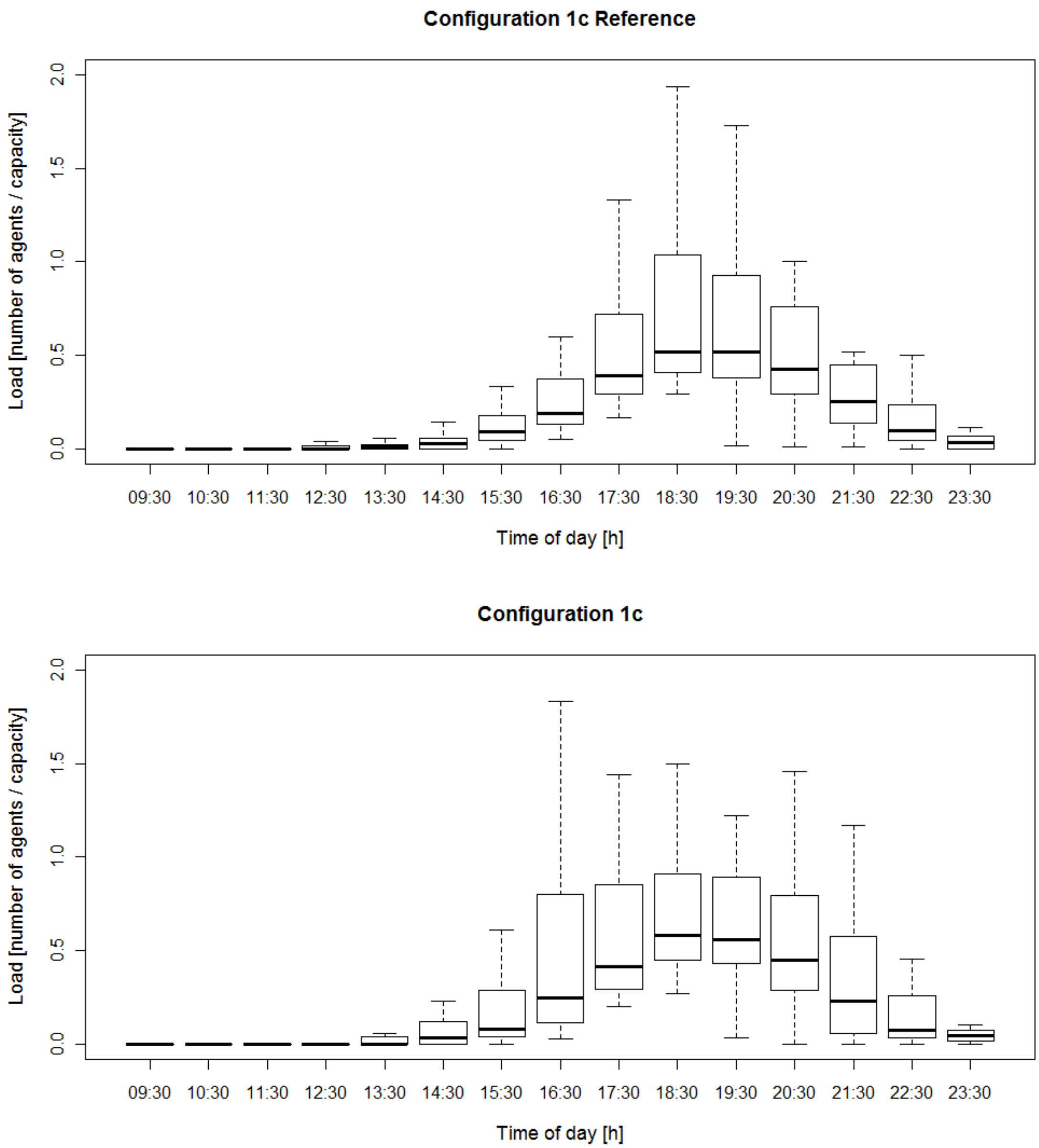
Figure 15 Boxplots of the load during the course of the day after 500 iterations



In comparison to configuration 0, the interquartile ranges for times with higher occupancies are smaller with configuration 1b. In addition, there are higher loads observed in the afternoon since agents prepone their discretionary activities to reduce the agent interaction penalty. With configuration 2 where agents can optimise the shopping or leisure destination choice, the loads in the afternoon decrease again since rescheduling activities is not the only option to avoid an agent interaction penalty. Obviously, agents start to concentrate their activities in facilities where no agent interaction penalty accrues. Therefore, facilities tend to be either not occupied at all or to be optimally crowded and there is substantially less variation of the loads per time step. This effect is increased through shorter shopping and leisure activity durations with configuration 2, as illustrated in Figure 11.

In order to examine the sensitivity of the agent interaction model towards the capacity definition and to have a closer look at the effects of the under-arousal penalty in a very lowly crowded setting, the capacities were doubled for configuration 1c. Figure 16 shows selected boxplots of the load during the course of the day after 500 iterations for configuration 1c and a configuration called *1c Reference*. Configuration *1c Reference* uses the same setting as configuration 0, but the facilities have two-time higher capacities. This allows for a comparison with configuration 1c and the observation of the effects associated with doubled capacities.

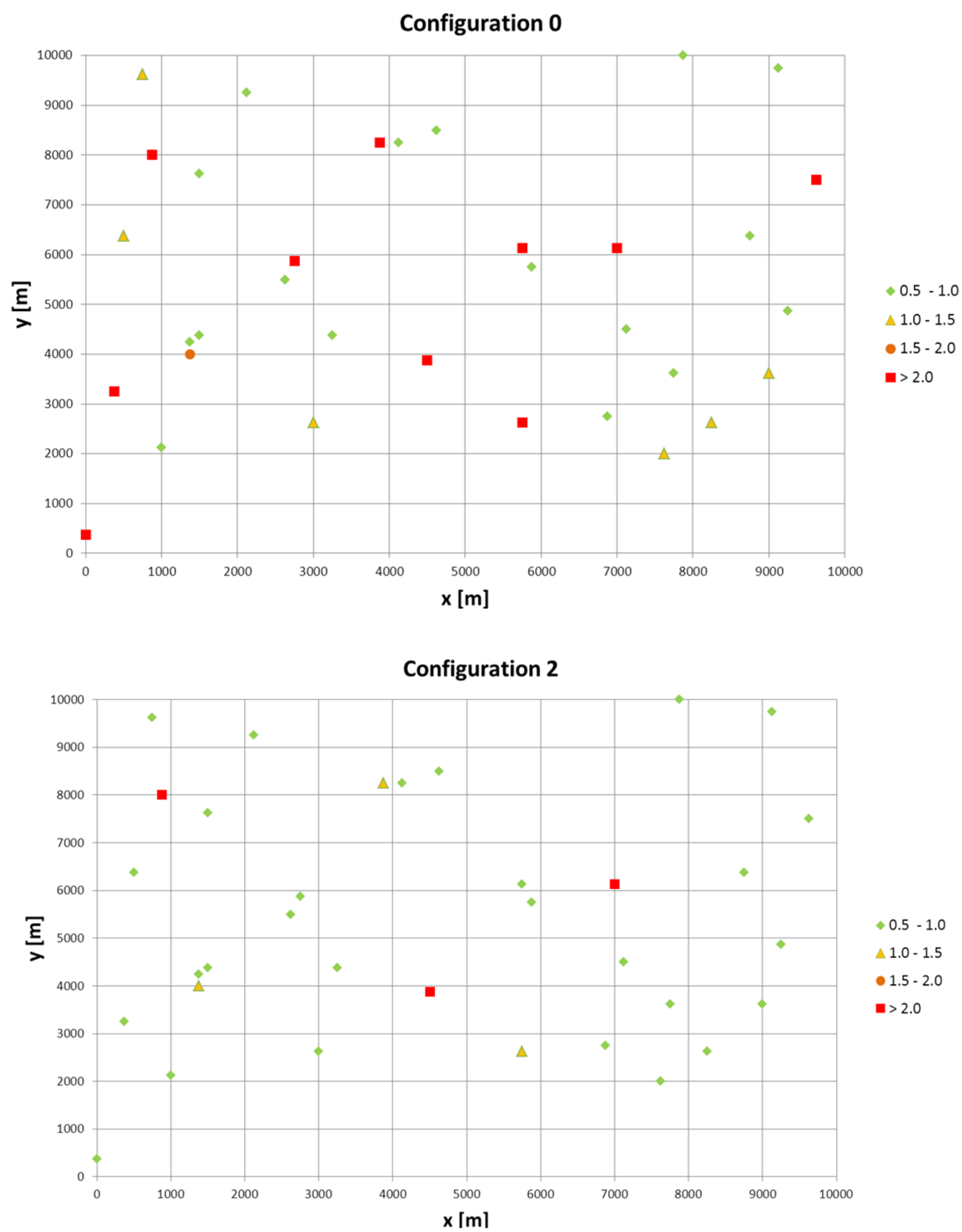
Figure 16 Boxplots of the load during the course of the day after 500 iterations for configuration 1c



Adding the agent interaction model to the scoring function in a setting with doubled capacities leads to a similar result as observed in Figure 15. The interquartile ranges for times with higher occupancies are smaller and there are higher loads observed in the afternoon. The maximum average load observed with configuration 1c is reduced by over 55%. Nevertheless, there are some differences regarding activity durations in comparison the simulation runs with “normal” capacities. Activity durations for discretionary activities with configuration 1c remained stable or even increased up to 7%. This is plausible since reducing activity durations would also increase the chance of performing an activity in a setting where an under-arousal penalty accrues.

Figure 17 gives an overview of the spatial occupancy. Every facility is plotted with a symbol according to their load at 18:30 o'clock.

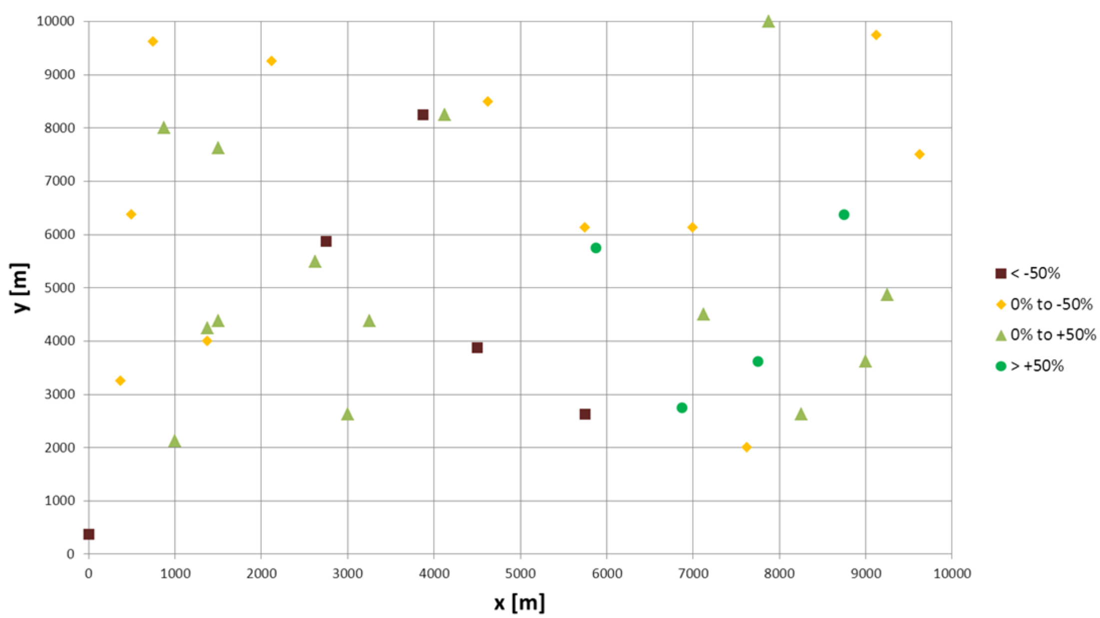
Figure 17 Current load at 18:30 for configuration 0 and 2



There is no spatial pattern observable regarding the load changes from configuration 0 to configuration 2. The number of overloaded facilities at 18:30 o'clock is reduced considerably with configuration 2. Nevertheless, the capacity is still exceeded for some facilities.

Figure 18 illustrates the change in number of visitors per day with configuration 2 in comparison to configuration 0.

Figure 18 Variation of number of visitors per day with configuration 2 in comparison to configuration 0

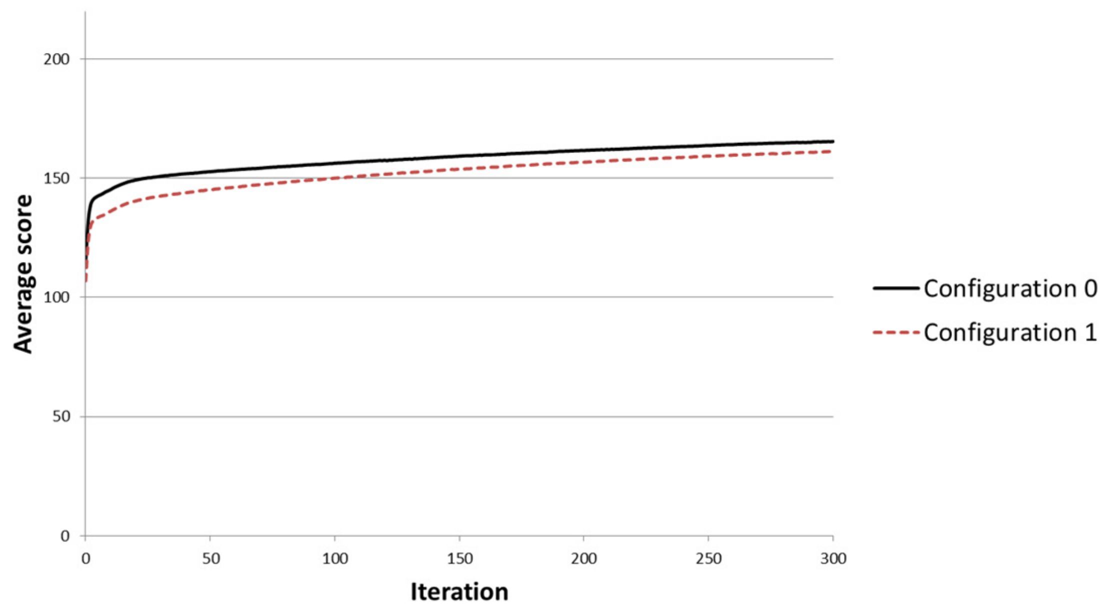


Similar to Figure 17, it is not possible to identify a spatial pattern produced by the agent interaction penalty in combination with the addition of destination choice to the simulation. Facilities in the peripheral areas tend to be less frequented. This is plausible since agents look for a discretionary activity location that allows them for a reduction in travel time. Due to the agent interaction penalty this is not excessively applied since agents have to factor in agent interaction.

6.2 Real-world scenario

In Figure 19, the development of the average score during the iterations is shown.

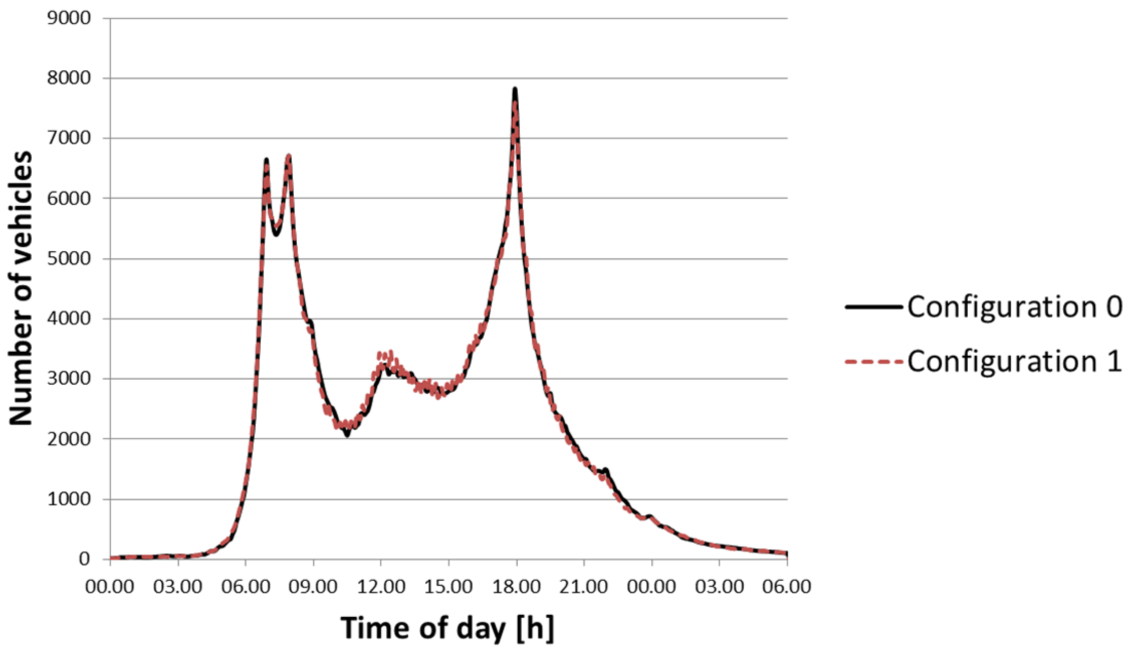
Figure 19 Development of average score during the iterations



During the iterations, there is only a small increase of the average score observable with both configurations due to the limited choice dimensions and already high initial plan scores. The average score with configuration 1 is always smaller than with configuration 0 due to the introduced agent interaction penalty, but the score difference decreases during the relaxation process.

Figure 20 illustrates the flow in the system during the course of the day after 300 iterations with configuration 0 and 1.

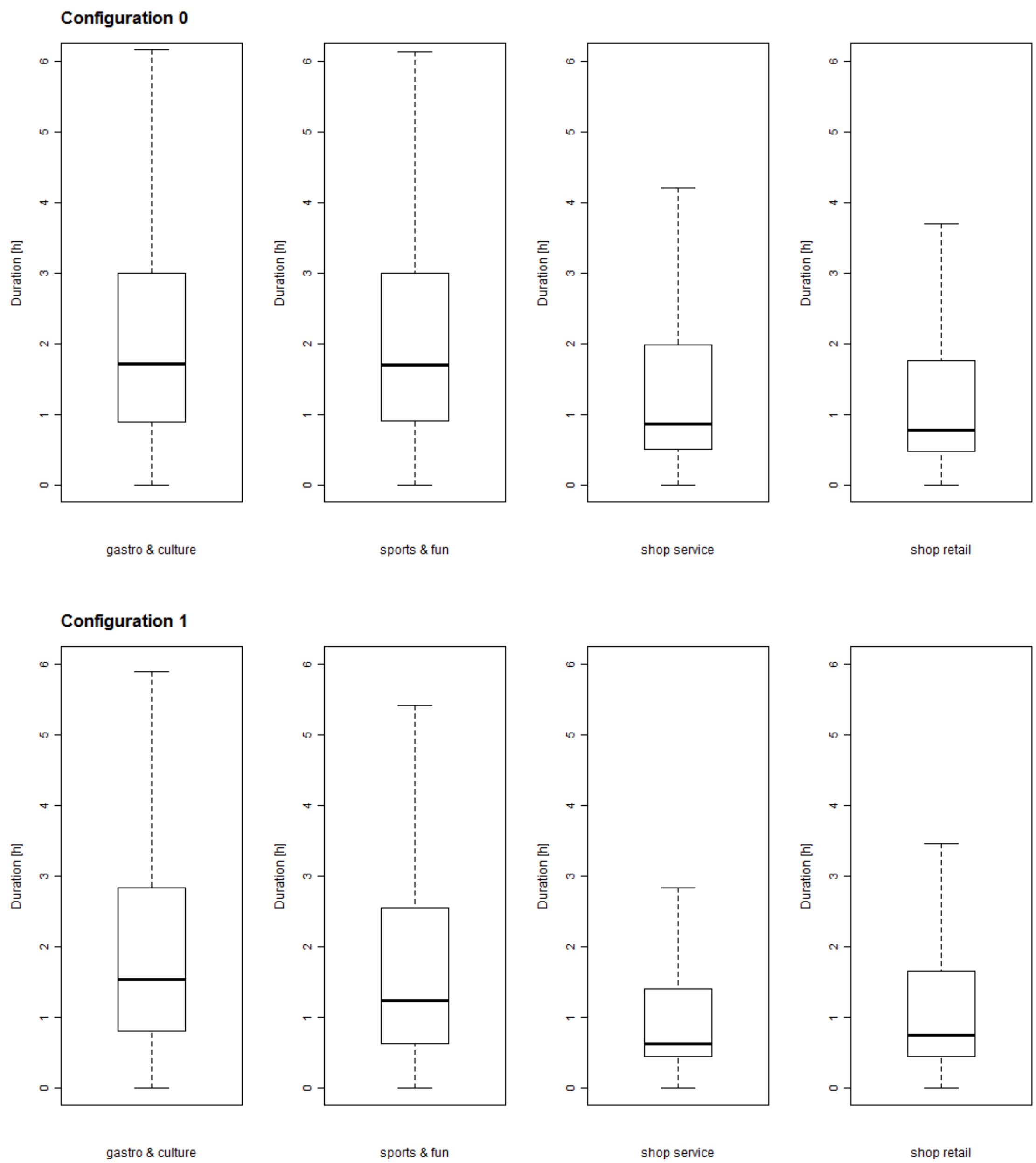
Figure 20 Flow in the system during the course of the day after 500 iterations



Similar to census data in reality (Swiss Federal Statistical Office 2007), it is possible to identify the morning-, the evening-, and the smaller midday-peak with both configurations which yield very similar resulting flows. A slightly higher midday-peak is observed with configuration 1. A small share of agents is still en-route after midnight.

In Figure 21, boxplots of the durations for discretionary activities after 300 iterations are plotted.

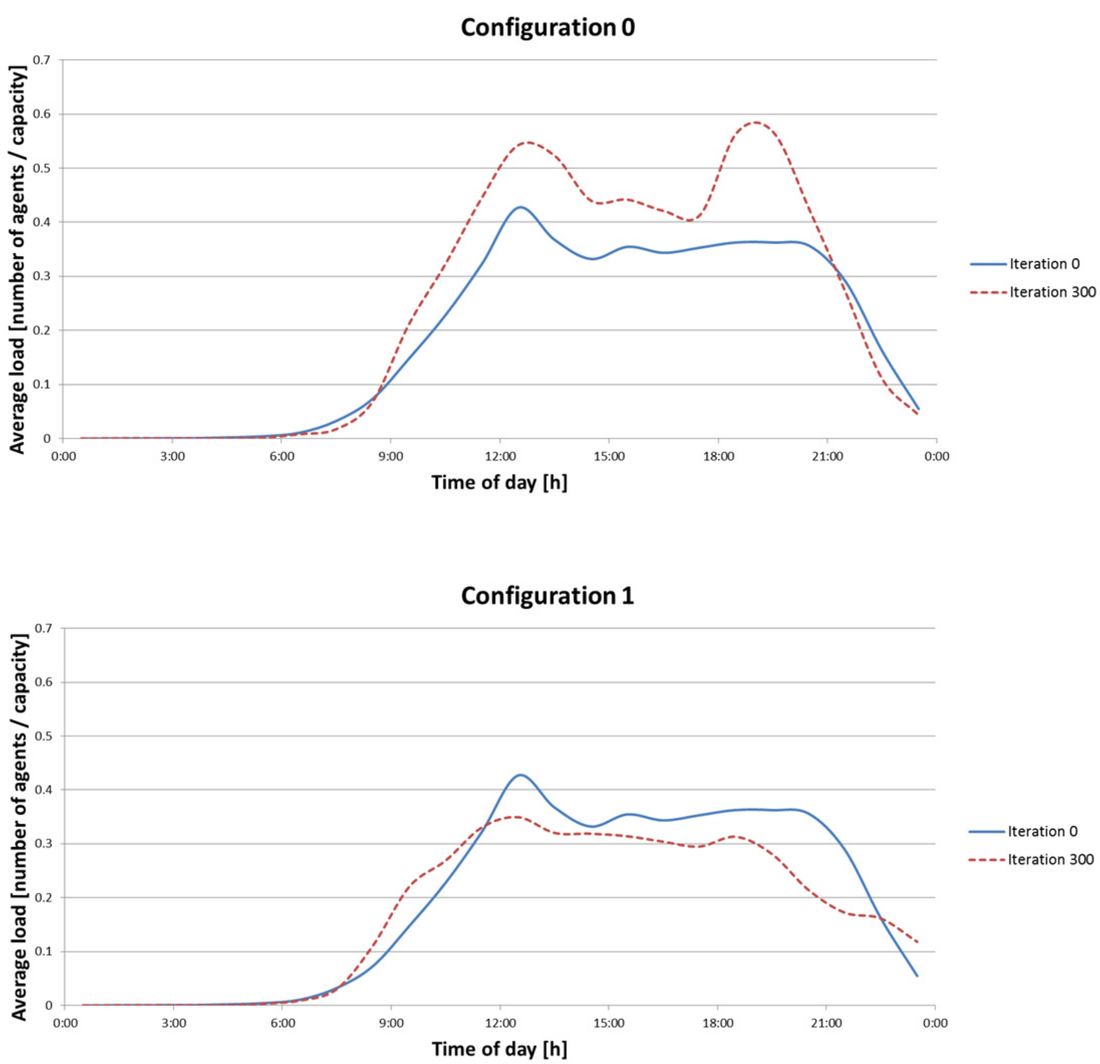
Figure 21 Boxplots of the durations for discretionary activities after 300 iterations



Adding the agent interaction model leads to a slight decrease of durations for discretionary activities. Whereas the reduction for *shop retail* and *gastro & culture* activities is within a range of 5%, the average time-reduction for *shop service* and *sports & fun* amounts to 15%. In addition, durations with configuration 1 are less widely distributed and less variation between the durations is observed.

In Figure 22, the average load of all discretionary activity facilities located within a circle with a radius of 12km around the centre of Zurich (Bellevue) for iteration 0 and 300 is shown. Similar to the analysis of count data, facilities outside of this circle are not included in order to reduce boundary effects. There are 8'983 discretionary activity facilities within this circle which account for 10% of the 90'355 discretionary activity facilities modelled for Switzerland.

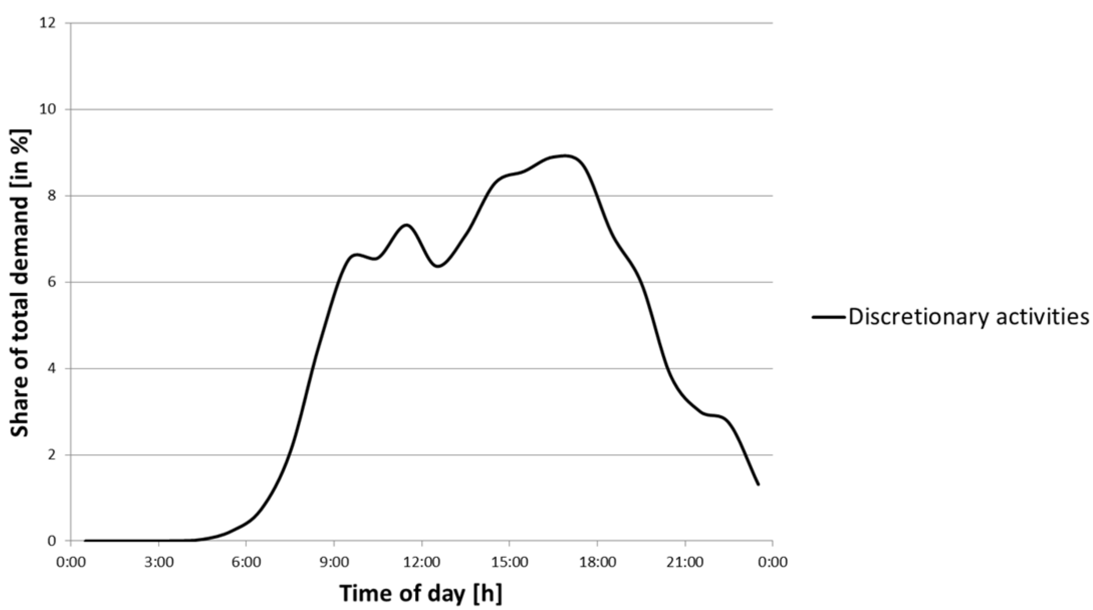
Figure 22 Development of average load of discretionary activity facilities



After iteration 0, the average load for both configurations is the same. There is a constant, high average load from 12 o'clock until 21 o'clock observed, peaking about noon. With configuration 0, two higher peaks at 13:30 and 19:30 emerge while the relaxation process is run. Adding the agent interaction model to the scoring function (configuration 1) leads to a reduction of the average load during the course of the day after 300 iterations. In addition, the two peaks observed with configuration 0 are extenuated and the average load curve is widened.

For comparison, discretionary activity demand (including shopping and leisure activities) during the course of the day according to Microcensus 2005 is shown in Figure 23 (Swiss Federal Statistical Office 2007). It is assumed that the average load curve of discretionary facilities in reality shows a similar pattern. Therefore, the average load curves shown in Figure 22 are compared to the demand curve illustrated in Figure 23.

Figure 23 Discretionary activity demand during the course of the day according to Microcensus 2005

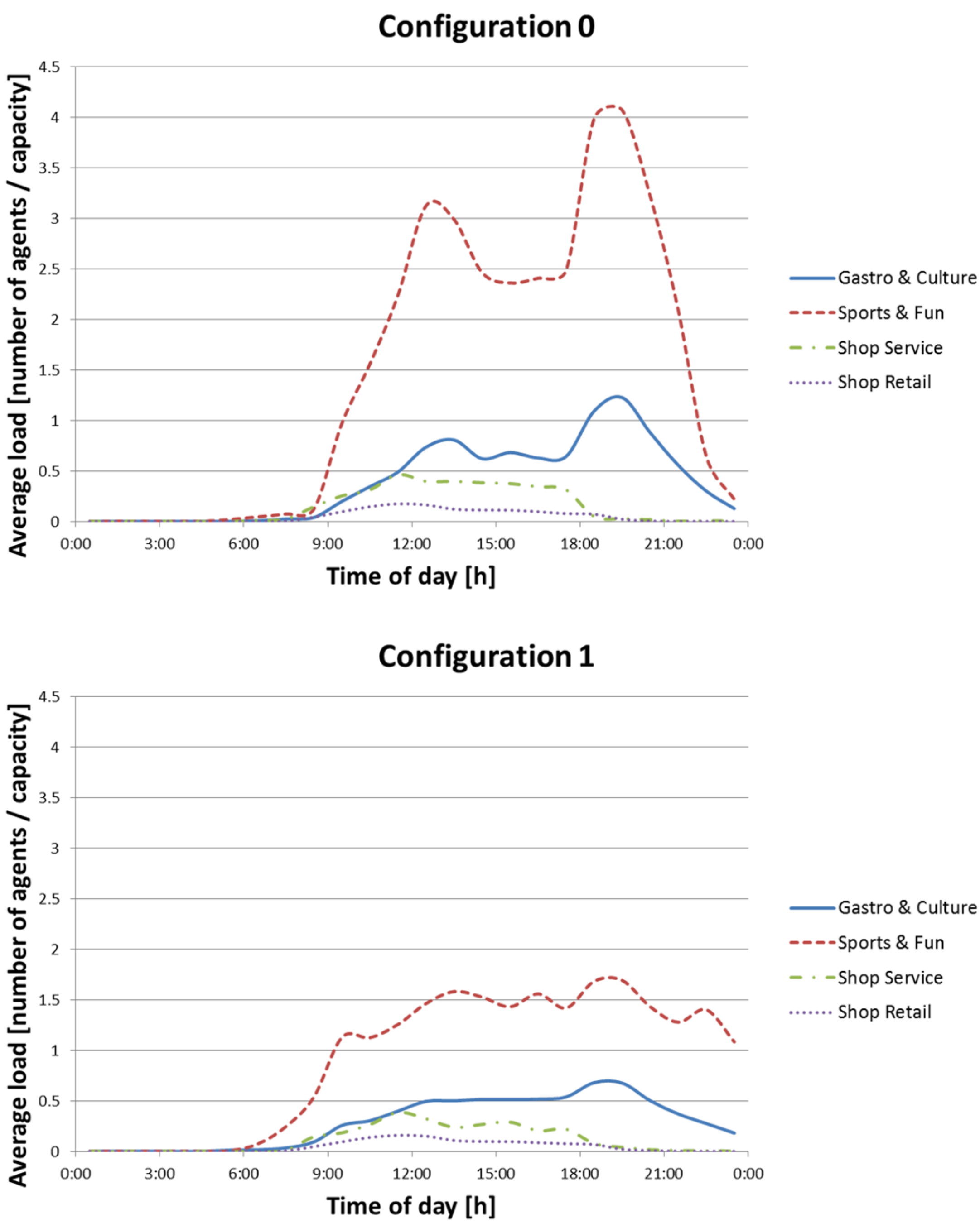


Source: Swiss Federal Statistical Office (2007)

The demand curve for discretionary activities is characterized by two peaks, one smaller midday-peak and a higher peak in the evening. The two high peaks of the average load curve with configuration 0 in Figure 22 are too pronounced in comparison to the discretionary activity demand curve shown in Figure 23. Adding the agent interaction model (configuration 1) reduces the magnitude of the peaks and yields more plausible results but the average load curve does not increase again after 12:00 o'clock and the evening peak disappears. This can be explained by the available choice dimensions. Since destination choice is not allowed, agents can only pre- or postpone their discretionary activity. Therefore, the peaks are considerably reduced and more discretionary activities are performed in the afternoon. Similarly to the results of the synthetic scenario (see Figure 15), it can be expected that the addition of the destination choice to the available choice dimensions during the iterations leads to more pronounced peaks again.

A closer look at the occupancies of shopping and leisure facilities within the 12km circle around Bellevue is presented in Figure 24 where the average load is differentiated per activity class.

Figure 24 Average load per activity class after 300 iterations

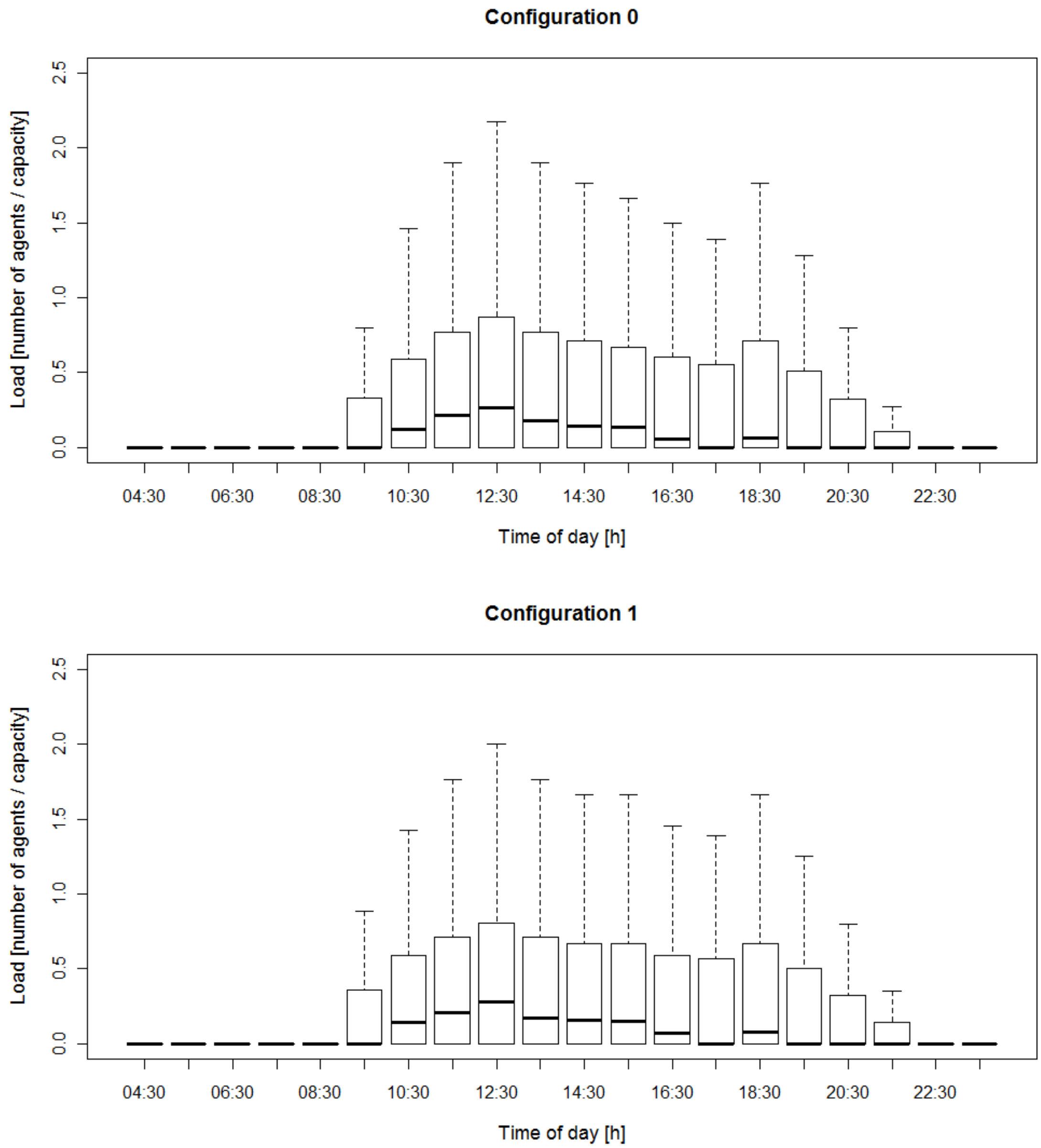


The average load curves are very different for the four discretionary activity types. *Shop service* and *sports & fun* facilities show higher levels of crowding with both configurations. This explains why a higher average activity duration reduction for *shop service* and *sports & fun* activities is observed in Figure 21. Since the facilities in these categories possess the highest average load curve, agents do not only reschedule their activities, but also shorten their activity durations.

The average load curves are lower with configuration 1 in comparison to configuration 0, except for *shop retail* facilities where the curves are almost identical. Despite the reduction, *sports & fun* and *shop service* facilities are overloaded in average from 9 o'clock until 24 o'clock and 18 o'clock, respectively.

In Figure 25, selected boxplots of the load during the course of the day for the facilities within the 12km circle around Bellevue after 300 iterations are shown. Facilities that are never occupied during the day are excluded. They account for 40% of all facilities located within the 12km circle.

Figure 25 Boxplots of the load during the course of the day after 300 iterations



Both plots look very similar. In comparison to configuration 0, the interquartile ranges are smaller with configuration 1b and the upper whiskers reach less far.

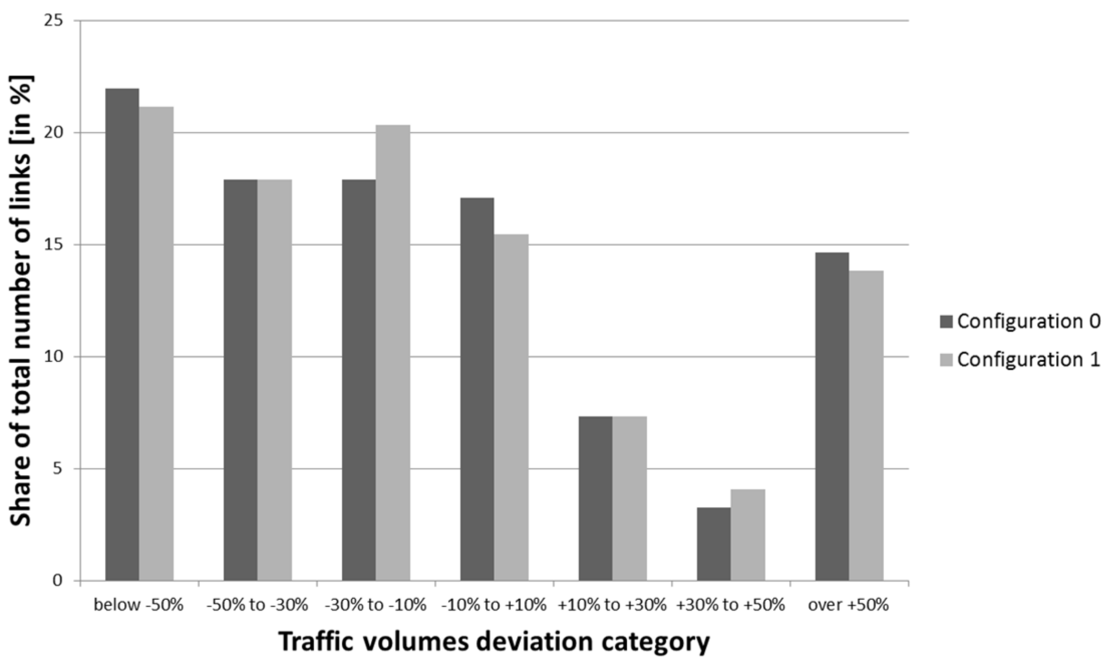
Figure 26 shows a histogram of the deviations of the simulated traffic volumes from count data. Seven categories are differentiated:

- *below -50%*:the simulated traffic volume is over 50% smaller than the count volume

- *-50% to -30%*: the simulated traffic volume is between 30% and 50% smaller than the count volume
- *-30% to -10%*:the simulated traffic volume is between 10% and 30% smaller than the count volume
- *-10% to +10%:*the difference between the simulated traffic volume and the count volume is not greater than 10%
- *+10% to +30%*: the simulated traffic volume is between 10% and 30% greater than the count volume
- *+30% to +50%*:the simulated traffic volume is between 30% and 50% greater than the count volume
- *over +50%*: the simulated traffic volume exceeds the count volume by over 50%

For every category the share of the total number of measured links is given.

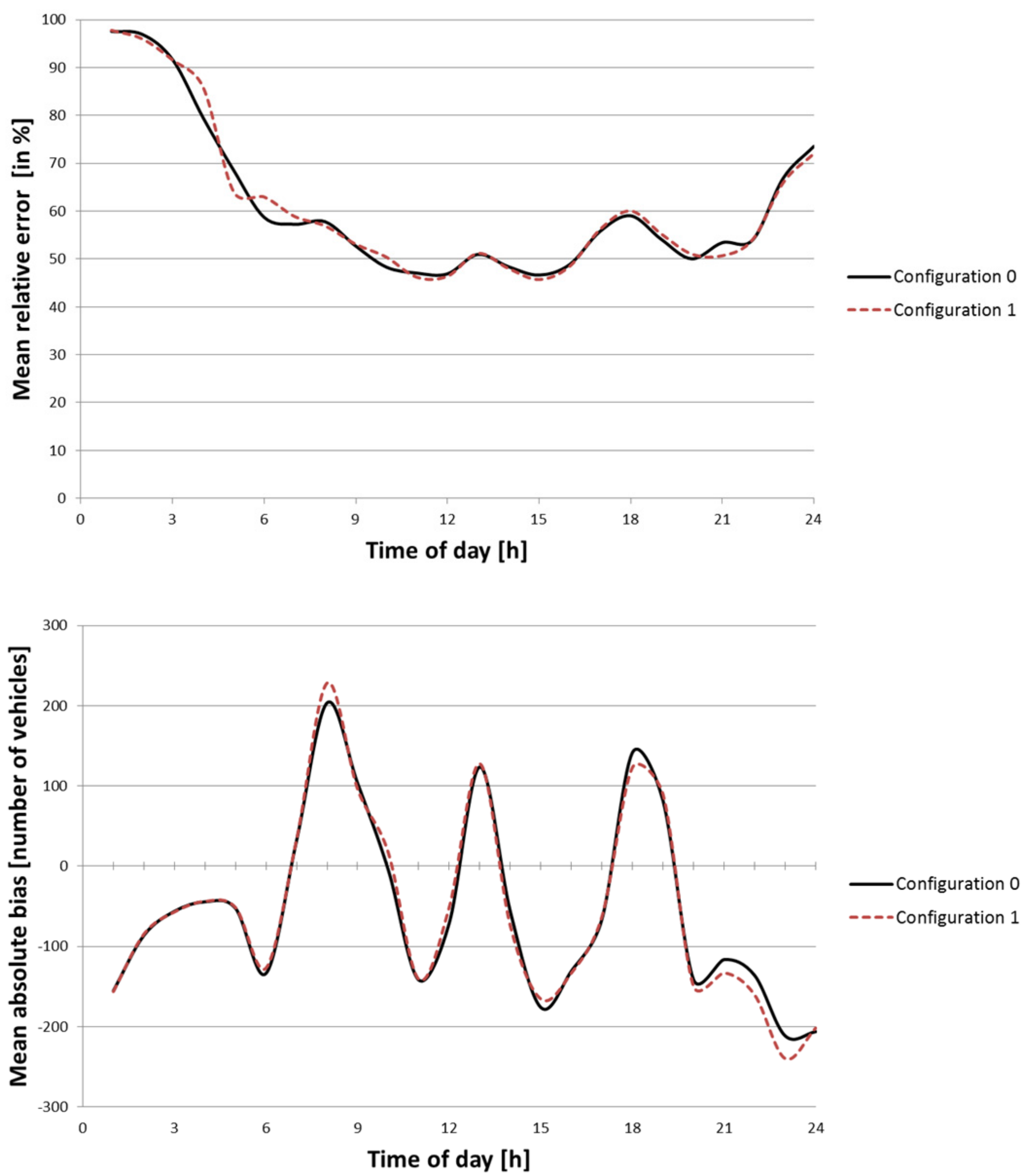
Figure 26 Histogram of traffic volumes deviations from count data



The histograms for both configurations 0 and 1 are very similar. Whereas a greater share of simulated link volumes differ more than 50% from count volumes with configuration 0, there are more simulated links that vary between *-30% to -10%* and *+30% to +50%* with configuration 1. About 15% of the links looked at in the simulation are within a range of *+/- 10%* of the counted volumes. A great share of the links in the simulation has a smaller traffic volume than counted in reality. This is plausible since freight traffic and demand traveling through, without performing an activity in the study area, are excluded in this thesis. The simulated traffic volumes differ by +/-41% from the counted volumes with both configurations. The corresponding median amounts to 37%. Comparable deviations are observed in other projects (e.g., Balmer et al. 2009).

In Figure 27, the mean relative error and mean absolute bias of the simulated traffic volumes in comparison to the real count data is shown.

Figure 27 Count data error plots



Both configurations 0 and 1 lead to very similar results. It can be seen that the deviation of the simulated volumes from the count volumes is even higher if the flow during the course of the day is analysed. The minimum mean relative error is reached at midday. The relative error is high in the early morning and late evening, whereas the absolute error decreases during these periods because the absolute traffic volumes are very small during these hours.

7 Conclusions

7.1 Main findings

Simulation results of the synthetic small-scale scenario indicate that the developed agent interaction model is a valuable tool for implementing agent interaction effects into MATSim. The model makes it possible to reduce implausibly overloaded facilities, as illustrated in Figure 15. In addition, agent's score is lowered in cases where they carry out a discretionary activity when only few agents are present. Thus, agents performing an activity in a location with an optimal level of crowding are rewarded.

Based on the results of the mini scenario, it can be concluded that the agent interaction parameter set applied with configuration 1b suits better. In comparison to the parameter set employed with configuration 1a, where the marginal utilities are ten-times higher, activity durations remained relatively stable (see Figure 10).

Validation with the real-world scenario confirmed that the agent interaction model is an applicable tool for the incorporation of agent interaction effects. Nevertheless, the raised question at the beginning of work, if simulation quality is increased through the implementation of agent interaction effect, cannot be answered conclusively since further validation has to be conducted. The introduction of the agent interaction model did not lead to less variation of the simulated traffic volumes in comparison to the counted volumes. There are very small traffic volume changes observable (see Figure 20) and these disappear in the random noise due to the stochastic variation of MATSim. Therefore, the difference between simulated traffic volumes and counted volumes are almost not affected by the agent interaction model. Nevertheless, simulation quality is increased in terms of facility loads since implausibly under- and overloaded locations are reduced.

Two critical aspects of the agent interaction model are identified. In the following, each aspect is discussed shortly.

Capacity definition

A central issue for modelling agent interaction in the activities infrastructure is the definition of capacities since they determine the thresholds for penalizing agents when performing an activity under the presence of other people. The whole agent interaction model is very sensitive to changes of this control variable. Therefore, the appropriate definition of capacities is of great importance. Two different challenges have to be taken into account. One challenge is to conceptually define the capacity. This might be very easy for activities infrastructures such as restaurants where the number of seats clearly determine the capacity, but for other activities infrastructures such as natural parks it is very difficult to determine the capacity limit. Another challenge is the implementation based on available data once the capacity is conceptually defined.

In this thesis, assumptions are made to resolve both challenges since real data on the capacity of activity facilities are not available. Capacity is defined based on the number of employees or the sales area. Consistency in the definition of capacity is reached because capacity differences between infrastructures can be correctly weighted through the difference in number of employees or sales area.

According to the simulation results, *shop service* and *sports & fun* facilities have higher loads than *shop retail* and *gastro & culture* facilities. These differences have to be further examined. It makes sense that *sports & fun* facilities have higher loads since people usually perform those activities in bigger groups and prefer facilities with higher loads, but only to the point where the capacity limit is reached.

Activity durations & Opening times

The addition of the two agent interaction penalty terms into the scoring function influences agent's overall behaviour. If destination choice is not permitted, agents react through adapting plans in the time dimension. They can apply the following strategies:

- pre- or postpone their shopping or leisure activity
- reduce the activity duration

The agent interaction parameter set has to be carefully chosen because otherwise the two strategies are excessively applied, shopping or leisure activities are pre- or postponed to times outside of the opening times or activity durations are reduced well below the desired activity durations that are derived from census data. Results of the mini scenario show that activity durations decreased the most with configuration 2 where destination choice is available during the iterations. Further validation regarding these issues is necessary.

7.2 Limitations

The agent interaction model is limited to agent interaction in the activities infrastructure itself. For instance, interaction effects in the parking infrastructure are not explicitly modelled. Nevertheless, they are implicitly incorporated through the over-arousal penalty that penalises agents performing an activity in a very crowded setting.

Furthermore competition/agglomeration effects on the supply side are omitted. Those effects can actually not be counted as agent interaction effects in the activities infrastructure since they depend on the configuration of activities infrastructures in the spatial system itself. Nonetheless they influence agent's destination choice and consequently change infrastructure occupancies.

The quality of the presented validation results is also subject to limitations. Some biases are introduced since only 10% of the population in the study area of the Zurich scenario are simulated. One agent simulated represents 10 people in reality. Therefore, occupancies of facilities can only change in intervals of 10. Since some facilities have a capacity smaller than 10 (e.g., some *shop service* stores), the load is always exceeded for those facilities if at least one agent is present. Agents staying at a facility with a capacity smaller than 10 cannot avoid an agent interaction penalty because destination choice is not permitted in the settings employed for validation. Similar problems have been observed in previous studies for occupancies of small buses where the buses were either fully occupied or not occupied at all.

8 Outlook

As mentioned in section 7, further validation of the agent interaction model is necessary. The Zurich scenario has to be run with destination choice as a choice dimension in order to examine the effects associated with it. In this context, changes in activity durations should be analysed since variation of activity durations showed to be the highest with destination choice available in the small-scale scenario.

More data on the capacity of discretionary activity facilities should be collected in order to calibrate the capacities defined in this thesis. For *shop retail* activities it might be interesting to use the area approach up to the point where agents start to check-out and then change to approach based on the number of employees since this is the limiting factor when agents check-out.

Furthermore, the incorporation agglomeration/competition effects on the supply side might enhance the agent interaction model and should be considered for future work.

Finally, updating supply and demand input data to date would be desired. There are new editions of the Federal Enterprise Census and the Microcensus as well as new count data of the Federal Roads Office and the city of Zurich available.

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