Integrating housing and transport interactions: A strategic dynamic approach

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Abstract

Urban areas face challenges like traffic congestion and resident relocation, underscoring the need for tools to manage the complex relationship between transport and land-use. Land-use Transport Interaction (LUTI) models explore these interrelations. In traditional approaches, transitions between future states are often overlooked. Capturing time lags between urban processes—such as travel mode changes (fast), residential relocation (medium), and infrastructure developments (slow)- is particularly challenging. We propose a dynamic simulation model over a multi-year horizon, explicitly capturing feedbacks between transport and land-use within a unique framework. Our approach is based on the principles of System Dynamics, which is well-suited for modelling complex systems but remains underutilised in LUTI research. Model application is showcased by an illustrative example, simulating residents' travel and residential location choice behaviour in a region. Some results from the case of Luxembourg will be presented in the conference session. The framework can evaluate various policies, offering valuable insights for transport and urban planning.

Keywords

Decision Support tool; Dynamic modelling; Land-use transport interactions; Mobility management; Transport economics and policy.

Suggested Citation

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Contents

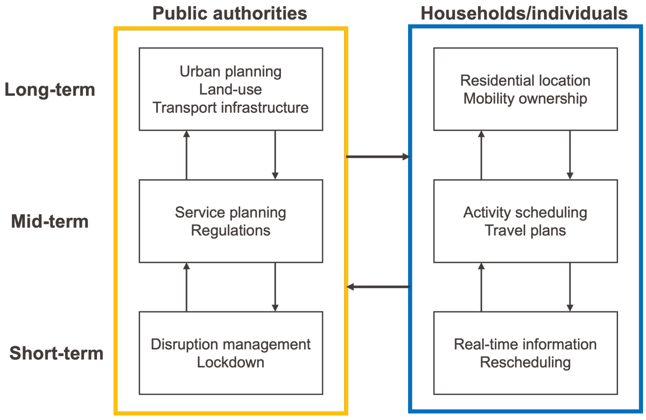
List of Tables

List of Figures

1 Introduction

Think of an urban area where individuals are living in. The urban context is a combination of choices with (i) different time horizons such as short-term, mid-term, and long-term, and (ii) different autocratic levels such as choices of household/individuals, or choices of public authorities. Thus, there are various decisions made at different temporal, spatial, and hierarchical level. Figure 1 presents example choices and decisions in different temporal and hierarchical level with their interactions.

Figure 1: Choices and decisions in urban context



More than 50% of the world's population now live in cities worldwide. Urban areas face challenges stemming from the interplay of transport and land-use developments like congestion, accessibility issues, increasing housing prices, housing shortage, relocation of residents, and migration. As transport and land-use planning are highly interdependent, a comprehensive model accounting for their interrelations is required. Effective urban planning demands a "What if?" forecasting capability to predict the most likely development paths for a given region over time, enabling decision-makers to implement effective strategies towards fined goals.

The interactions between transport and land-use are not effectively captured in conventional transport planning models, as land-use is usually treated exogenously. One methodology to combine transport and land-use sub-models is land-use transport interaction (LUTI) models (Wegener, 2021; Black, 2018; Waddell, 2014). They are used to assess the impact of exogenously given transport and land-use policies (e.g., expanding transport infrastructure, new housing developments, changes in public transport provision and fares). They also are used to investigate socio-demographic developments (e.g. population growth, migration) and economic scenarios (e.g. economic growth/decline). The first operational land-use models were based on analogies to physics such as gravity models (Lowry, 1964). Random utility models originating from micro-economics (Lee and Waddell, 2010; Yang *et al.*, 2013; Kim *et al.*, 2005), bid-choice theory (Hurtubia and Bierlaire, 2014; Martinez, 1996), micro-simulation or agent based models (SALVINI and MILLER, 2005), and cell-based automata where transition probabilities are used to update land-use over time (Lau and Kam, 2005) are example approaches used in more recent studies. LUTI models combine transport and land-use sub-models.

Although the current LUTI studies provide ample insights into integrating transport and land-use, there are limitations that can be improved: (i) As in traditional transport modelling, conventional LUTI models follow the notion of equilibrium, assuming the urban systems are always in a state of equilibrium. However, this is not realistic assumption as the urban systems might not ever reach equilibrium. (ii) The connection between the future projections and current conditions is neglected, as the pathway to future states is unknown. (iii) The aggregate effects for strategic decision-making is overlooked. Addressing these face challenges: (i) Explicit modelling of the dynamics between land-use and transport systems is complicated, as changes within the two systems occur at different speeds having a wide spectrum ranging from fast (e.g. transport users), to medium (e.g. residential location), to slow (e.g. transportation systems and land-use) changes. For example, land-use and transport systems change relatively slowly due to their considerable inertia, as they are tied to physical structures. (ii) All these processes have their own reaction speed and thus, it is important to take their individual time lags into account.

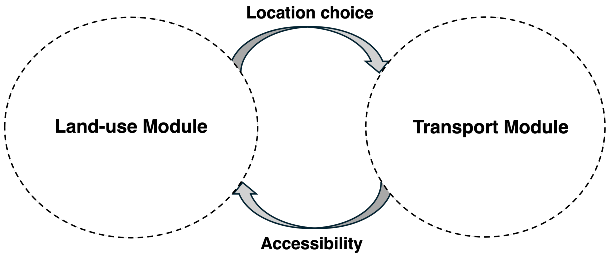
In this paper, we propose a dynamic simulation model for transportation and land-use over a time horizon of multiple years. The model's timestep is days so the time delays and reaction speeds of different processes can be effectively captured. We integrate transport and land-use models within a unique framework, simulating the state of the transport and land-use systems over time, explicitly accounting for their interactions. On the land-use side, this study focuses on residential location choices and treats workplace as exogenously given in the model. The framework is developed at an urban zonal level to simulate the transport and land-use dynamics between different zones of urban areas through time. Our approach is based on the principles of the System Dynamics (Sterman, 2000). Our framework contributes to the state-of-the-art in LUTI modelling by: (i) not being based on the notion of urban equilibrium, (ii) modelling both transport and land-use endogenously within the same framework, (iii) capturing interaction and feedback mechanisms explicitly, (iv) dynamic modelling, thus captures the development path over time needed for decision support tools, (v) taking into account time lags between entities by determining the state of the systems through dynamic simulation., (vi) eliciting the structure that drives the system behaviour, and (vii) being computationally quick. This is an intentionally developed strategic aggregate model. The proposed framework is s decision-support tool, serves to anticipate future trends and investigate the consequences of policy reforms, considering the inter-connected dynamic effects of transportation, congestion and accessibility, housing prices, land constraint, and population dynamics.

The remainder of this manuscript is structured as follows. The integrated framework is discussed in Section 2. An illustrative example is presented in Section 3 to showcase the capabilities of the proposed framework. The concluding remarks and opportunities for future research are discussed in Section 4.

2 Methodology

We propose a modelling framework to jointly simulate the transport and land-use dynamics over a time horizon of multiple years. This framework make use of transport manuals, econometric, and behavioural models. The integrated framework consist of 2 modules: transport module, and land-use module. The transport module is fed to the land-use module through accessibility, which is the potential to reach workplace and service opportunities. The land-use module is linked back to the transport module through location choice. Figure 2 presents the general structure of inter-relationships between these modules.

Figure 2: General structure of the integrated framework



This framework is based on the principles of systems dynamics (SD) (Sterman, 2000) and synergetics (Haken, 1983). Some specifications of the framework are as follows: (i) The temporal time steps are days. (ii) The spatial aspect is analyzed at the level of discrete urban zones. (iii) Attractivity of the whole area and migration is assumed exogenously given. (iv) Travel times and travel costs are endogenously updated within the model.

(v) Renting is considered as the means to satisfy the housing demand. (vi) Rent and land prices are identified endogenously based on amount of demand and supply at each time-step.

2.1 Causal loop diagrams

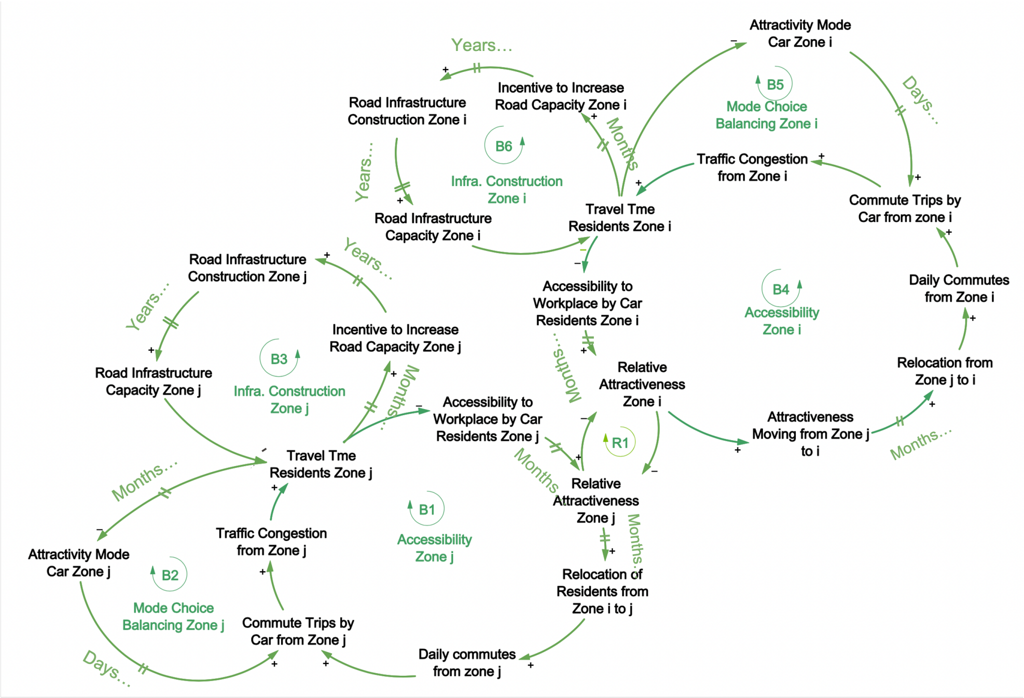
The system modelled in the study is composed of various sub-systems. Our mental models often fail to include the critical feedbacks determining the dynamics of the system. To represent the feedback structure of the system of interest, causal loop diagram consisting of variables connected by arrows denoting the causal influences among the variables are developed using the Vensim PLE simulation software (Ventana Systems, 2025), with the output shown in Figure 3). In causal loop diagrams, delays are indicated by double slashes `"//"` on the causal arrows.

Consider a region with two residential zones i and j. In the transport module (Figure 3(a)), an increase in the commute time of residents of zone i, decreases the accessibility of its residents to their workplaces leading to a reduction in the relative attractiveness of residential zone i and thus an increase in the relative attractiveness of residential zone j. This leads to an increase in relocation of residents from zone i to j, causing more daily commutes from zone j and thus increasing traffic congestion and travel time for residents of zone j, which leads to a decrease in its accessibility and attractiveness. Two balancing loops indicating change of transport mode choice and transport infrastructure expansion help decreasing the travel times. However, they each come with a delay which have different time lags.

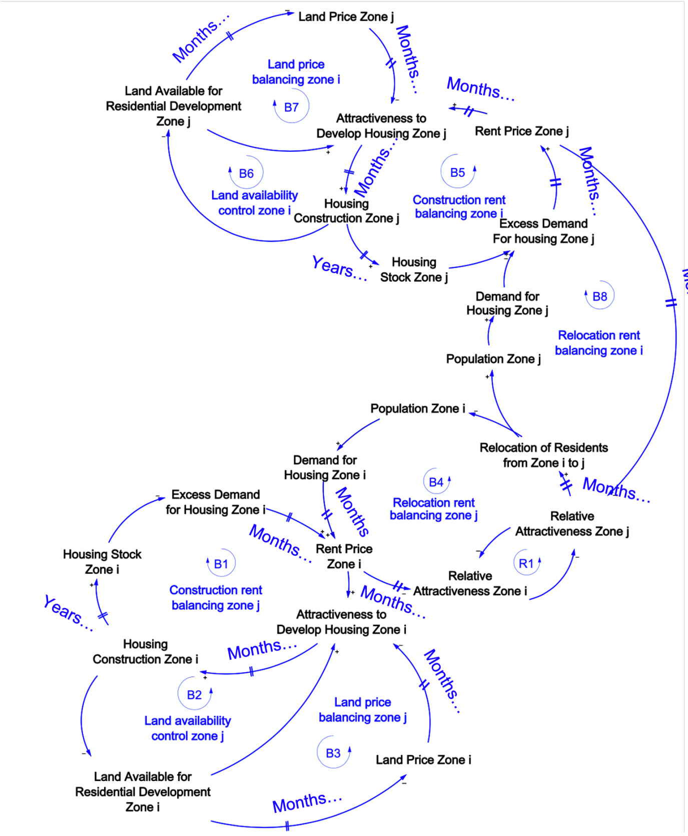
In the residential relocation module (Figure 3(b)), an increase in the population of zone i affects the demand for housing and can increase the rental prices, leading to increasing attractiveness for housing development. Land availability and increasing land prices control the housing development process. The construction of new housings decreases the excess housing demand with a time lag of construction time, controls the residential rent prices of zone i, increasing the relative attractiveness of residential zone i and relocation of residents to it, which affects the dynamics of other competing zone(s).

The population movement and relativeness attractiveness of the residential zones are the common variables between the transport and residential location module, joining these two modules and affecting their inter-related dynamics.

Figure 3: Causal loops in transport and residential relocation



(a) Causal loops in transport

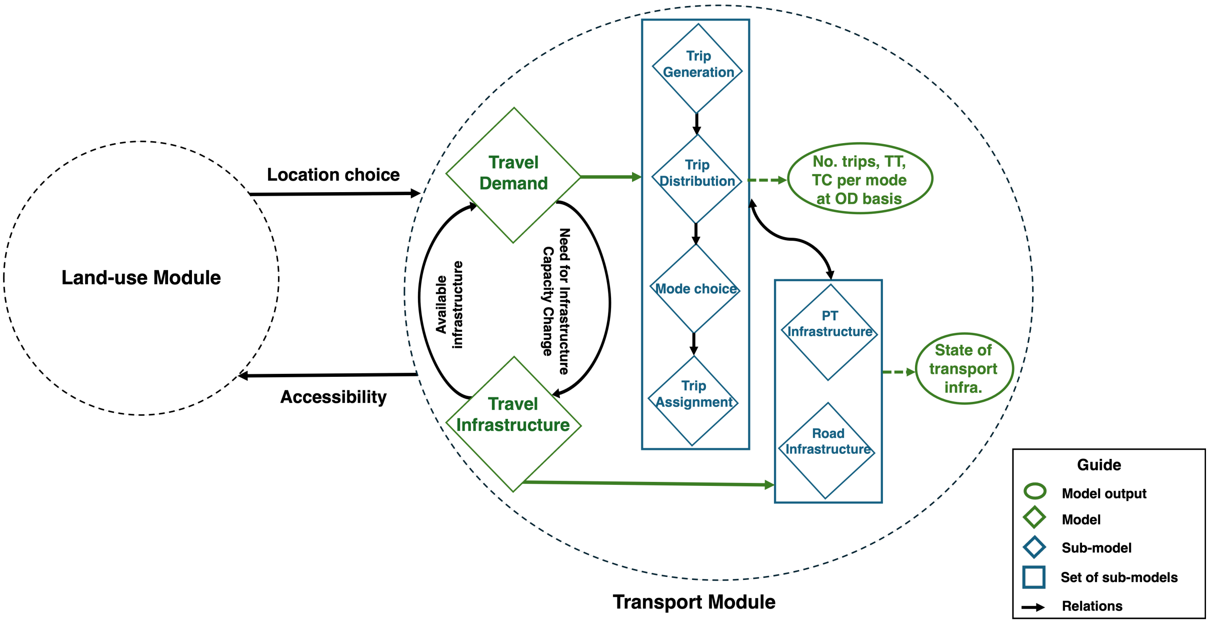


(b) Causal loops in residential relocation

2.2 Transport module

The transport module simulates the travel behaviour of the population and has two models; (i) a travel demand model, and (ii) a travel infrastructure model. The travel demand model simulates passenger travels, comprising 4 sub-models (i) trip generation, (ii) trip distribution, (iii) mode choice, and (iv) trip assignment. In this framework, travel demand is represented by trip generation volume in terms of average daily commute trips at morning peak hour.

Figure 4: Transport module



In the trip generation step, the number of trips originating from each zone is estimated. Commuting trips are driven by the employed population, and only morning peak-period trips are considered. A trip rate method is used, where the number of employed residents in a zone is multiplied by a fixed commute trip rate per person on a typical workday:

$$T_i(t) = N^{\mathrm{Empl}}(t)\lambda_{\mathrm{Trip}}^{\mathrm{Peak}} \tag{1}$$

where $T_i(t)$ is the number of morning peak-period commute trips originating from zone i at timestep t, $\lambda_{\mathrm{Trip}}^{\mathrm{Peak}}$ is the average commute trip rate per employed individual during the morning peak, and $N^{\mathrm{Empl}}(t)$ is the number of employed residents in zone i at time t.

In trip distribution, the generated trips are allocated to destination zones. This allocation is performed using a gravity model (Ortúzar and Willumsen, 2011), a spatial interaction model commonly employed in transportation planning to estimate how trips are distributed from origins to destinations. Given the total number of trip productions $T_i(t)$ from each origin zone i, raw attractiveness values $A_j(t)$ for each destination zone j (e.g., number of jobs in zone j), and a generalised travel cost matrix $\mathrm{GC}_{ij}(t)$ between zones, the production-constrained gravity model (singly constrained to origins) is expressed in Equation 2.

$$T_{ij}(t) = T_i(t) \frac{A_j(t)\ \mathrm{FF}(\mathrm{GC}_{ij}(t))}{\sum_k A_k(t)\ \mathrm{FF}(\mathrm{GC}_{ik}(t))} \tag{2}$$

where $T_{ij}(t)$ denotes the number of morning peak-period commute trips from origin zone i to destination zone j. The function $\mathrm{FF}(\mathrm{GC}_{ij}(t))$ is a deterrence function that decreases with increasing generalised cost, reflecting the diminishing likelihood of commuting to more distant or costly destinations. The denominator $\sum_k A_k(t)\ \mathrm{FF}(\mathrm{GC}_{ik}(t))$ acts as a normalisation factor, ensuring that the total trips from each origin zone i are proportionally distributed across all destinations based on their weighted attractiveness. The deterrence function $\mathrm{FF}(\mathrm{GC}_{ij}(t))$ is defined as an exponential decay form, commonly used in urban trip distribution models (particularly for work trips), as follows:

$$\mathrm{FF}(\mathrm{GC}_{ij}(t)) = e^{\beta_{\mathrm{GC}}\mathrm{GC}_{ij}(t)} = e^{\beta_{\mathrm{GC}}\left(\beta_{\mathrm{TT}}^{\mathrm{GC}}\overline{\mathrm{TT}}_{ij}^{(\Delta t_{\mathrm{perceive}})}(t)+\gamma\,\overline{\mathrm{TC}}_{ij}^{(\Delta t_{\mathrm{perceive}})}(t)\right)} \tag{3}$$

where β_{GC} is the impedance parameter that controls the sensitivity of trip distribution to generalised cost, estimated to fit data using Hyman method (Hyman, 1969). A higher value of β_{GC} implies that trip probabilities decline more rapidly with increasing generalised cost. $\mathrm{GC}_{ij}(t)$ is the generalised cost of traveling from origin i to j, expressed as a money-metric utility. $\overline{\mathrm{TT}}_{ij}^{(\Delta t_{\mathrm{perceive}})}(t)$ is the perceived average commute time, and $\overline{\mathrm{TC}}_{ij}^{(\Delta t_{\mathrm{perceive}})}(t)$ is the perceived average commute cost between zones i and j over the time period $\Delta t_{\mathrm{perceive}}$ at timestep t. $\Delta t_{\mathrm{perceive}}$ represents the time window over which the perception is averaged, capturing the information delay in the decision-making process, reflecting how travel time and cost are experienced by commuters over a specific time period rather than instantaneously. $\beta_{\mathrm{TT}}^{\mathrm{GC}}$ represents the value of time (Euro/min, used to convert time into monetary units. γ is a weighting parameter for the travel cost, normalised to 1 to maintain consistency with the money-metric utility formulation.

Once the generated trips are distributed across destination zones, mode choice is modelled using a logit framework. Mode choice modelling estimates the probability that an individual selects a specific transportation mode (e.g., car or public transport) from a discrete set of alternatives. Each mode is associated with a utility function that incorporates variables such as travel time and travel cost.

$$T_{ij}^{m}(t) = T_{ij}(t) \frac{e^{V_{ij}^{m}(t)}}{\sum_{m'} e^{V_{ij}^{m'}(t)}} \tag{4}$$

where $T_{ij}^{m}(t)$ denotes the number of morning peak-period commuters from origin zone i to j by mode m, and $V_{ij}^{m}(t)$ is the utility of mode m for that OD, defined as:

$$V_{ij}^{m}(t) = \beta_{\mathrm{TT}}^{m} \overline{\mathrm{TT}}_{ij}^{(\Delta t_{\mathrm{perc,Road}}),m}(t) + \beta_{\mathrm{TC}}^{m} \overline{\mathrm{TC}}_{ij}^{(\Delta t_{\mathrm{perc,Road}}),m}(t) \tag{5}$$

$\overline{\mathrm{TT}}_{ij}^{(\Delta t_{\mathrm{perc,Road}}),m}(t)$ is the perceived travel time by mode m from origin i to destination j at timestep t, averaged over the time period $\Delta t_{\mathrm{perc,Road}}$. $\overline{\mathrm{TC}}_{ij}^{(\Delta t_{\mathrm{perc,Road}}),m}(t)$ is the perceived commute cost by mode m from zone i to zone j at timestep t, averaged over the same time window $\Delta t_{\mathrm{perc,Road}}$. β_{TT}^{m} and β_{TC}^{m} are mode-specific utility parameters representing the disutility of travel time and cost, respectively.

Trips are analysed at the corridor level, with one corridor defined between each origin–destination pair. As a result, trip assignment is simplified, and only a single route is considered between each pair of zones.

In the transport infrastructure development model, aggregate speed–flow relationships are applied for each OD movement, based on formulations from transport planning manuals. The car commute speed between zones i and j during the morning peak at time t is given by:

$$\mathrm{V}_{ij}^{\mathrm{PC}}(t) = \frac{V_{ij}^{\mathrm{FFS}}(t)}{1 + \beta \cdot (\mathrm{DF}_{ij}^{\mathrm{PC}}(t))^{\alpha}} \tag{6}$$

where $\mathrm{V}_{ij}^{\mathrm{PC}}(t)$ is car commute speed from zone i to j at the morning peak at timestep t. $V_{ij}^{\mathrm{FFS}}(t)$ is free-flow speed, which is the average speed of vehicles in uncongested conditions. $\alpha = 10$ and $\beta = 0.2$ are scaling parameters based on the Highway Capacity Manual (Council, 2000). $\mathrm{DF}_{ij}^{\mathrm{PC,pk}}(t)$ is demand factor for private car traffic between zone i and j at morning peak at timestep t. $\mathrm{DF}_{ij}^{\mathrm{PC,pk}}(t)$ is computed as Equation 7.

$$\mathrm{DF}_{ij}^{\mathrm{PC}}(t) = \mathrm{DF}_{ij}^{\mathrm{PC}}(0) \frac{\mathrm{Cap}_{ij}^{\mathrm{PC}}(0)}{\mathrm{Cap}_{ij}^{\mathrm{PC}}(t)} \cdot \frac{C_{ij}^{\mathrm{PC}}(t)}{C_{ij}^{\mathrm{PC}}(0)} \tag{7}$$

where $\mathrm{Cap}_{ij}^{\mathrm{PC}}(t)$ is road capacity between zones i and j at timestep t. $\mathrm{Cap}_{ij}^{\mathrm{PC}}(t) \in (0, \infty)$ is expressed on a relative scale, where the initial capacity at the beginning of the simulation is set to 1. The capacity can subsequently take values lower or higher than 1 depending on network development. $C_{ij}^{\mathrm{PC}}(t)$ is number of car-based commutes from i to j at timestep t, calculated using the morning peak OD flows, $T_{ij}^{\mathrm{PC}}(t)$, and average car occupancy, $\mathrm{Occ}^{\mathrm{PC}}(t)$, as $C_{ij}^{\mathrm{PC}}(t) = \frac{T_{ij}^{\mathrm{PC}}(t)}{\mathrm{Occ}^{\mathrm{PC}}(t)}$. $\mathrm{DF}_{ij}^{\mathrm{PC}}(0)$ is the initial demand factor, used to initialise the transport model and defined as:

$$\mathrm{DF}_{ij}^{\mathrm{PC}}(0) = \sqrt[\alpha]{\frac{V_{ij}^{\mathrm{FFS}}(t) - V_{ij}^{\mathrm{PC}}(0)}{\beta \cdot V_{ij}^{\mathrm{PC}}(0)}} \tag{8}$$

where $V_{ij}^{\mathrm{PC}}(0)$ is the car speed at morning peak between i and j based on data sources such as Google Maps.

The decision to increase the road infrastructure capacity is determined based on a set of rules:

$$\text{If } \frac{\overline{C}_{ij}^{\mathrm{PC},(\Delta t_{\mathrm{dec}})}(t)}{C_{ij}^{\mathrm{PC}}(0)} \geq 1 + \theta^{\mathrm{PC}} \text{ and } \overline{V}_{ij}^{\mathrm{PC},(\Delta t_{\mathrm{dec}})}(t) \leq V_{ij}^{\theta,\mathrm{PC}}, \text{ then } \mathrm{Cap}_{ij}^{\mathrm{PC}*}(t) = \frac{\overline{C}_{ij}^{\mathrm{PC},(\Delta t_{\mathrm{dec}})}(t)}{C_{ij}^{\mathrm{PC}}(0)} \tag{9}$$

where $\overline{C}_{ij}^{\mathrm{PC},(\Delta t_{\mathrm{dec}})}(t)$ is the average number of commutes during the morning peak from zone i to$j$ at timestep t, averaged over the decision time window Δt_{dec}. This accounts for the fluctuations in commute patterns over time and provides a more stable estimate for decision-making regarding road expansion. $C_{ij}^{\mathrm{PC}}(0)$ is number of commutes at morning peak from i to j at the start of the simulation. θ^{PC} is a threshold for road capacity expansion (e.g., 0.25), indicating when the road needs expansion based on changes in the number of morning peak commutes. $\overline{V}_{ij}^{\mathrm{PC},(\Delta t_{\mathrm{dec}})}(t)$ is the average car speed during the morning peak from zone i to j at timestep t, averaged over the decision time window Δt_{dec}. $V_{ij}^{\theta,\mathrm{PC}}$ is minimum acceptable threshold speed. If the average speed falls below this threshold, it suggests that the road is congested and may need to be expanded. $\mathrm{Cap}_{ij}^{\mathrm{PC}*}(t)$ is the desired road capacity between zone i and j at timestep t, based on the decision criteria.

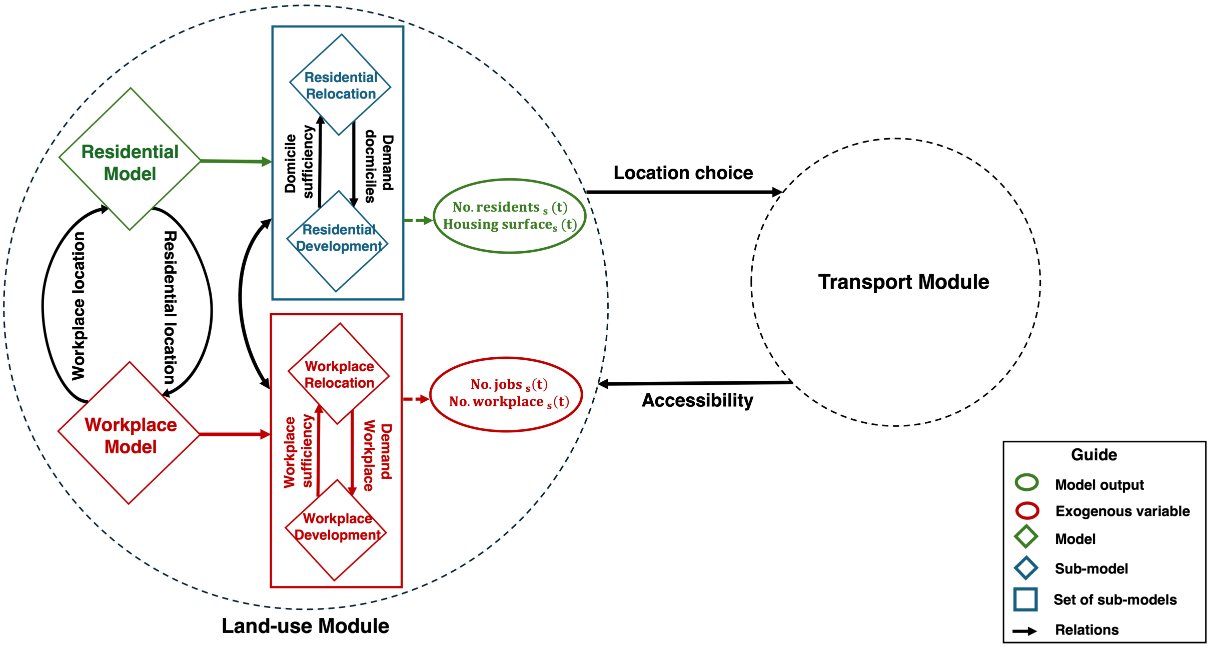
Public transport infrastructure development follows a similar rule-based approach, driven by demand during the morning peak and the capacity constraints of existing public transport links between zones.

The output of the transport module in each simulation step includes the number of trips at an origin-destination basis by each mode, mode shares, travel times and cost between each origin- destination pair, which links the transport module back to the land-use module through accessibility.

2.3 Land-use module

The land-use module simulates the dynamics of residential and workplace relocation and development, consisting of two models; (i) a residential model, and (ii) a workplace model (Figure 5). In the current framework, we focus only on the residential model and assume the workplace model as given and exogenous. In further operational extensions of the framework, the workplace model can be endogenised. The residential model has two sub-models; (i) a residential relocation sub-model (demand), and (ii) a housing development sub-model (supply). The major factor for housing development is the increase in housing demand due to increase of population. Housing development is also influenced by housing market factors such as housing prices and is constrained by land available for residential development.

Figure 5: Land-use module



The residential relocation sub-model simulates the relocation of residents within the study area in three steps:

(i) Out-migration of residents: The number of residents relocating from each zone is estimated based on the average duration of residence. The effect of residential rent prices on the decision to move out can also be incorporated.

$$\mathrm{mv}_i^{\mathrm{out}}(t) = \frac{N_i^R(t)}{\Delta T_i^{\mathrm{mv}}} \tag{10}$$

where $\mathrm{mv}_i^{\mathrm{out}}(t)$ is the move-out rate from zone i, $N_i^R(t)$ is the number of residents in zone i at time step t, and ΔT_i^{mv} is the average residence duration in zone i, estimated from housing survey data.

(ii) Pooling of movers: The total pool of potential movers in the region includes net births, net migration, and out-migration across all zones:

$$N_T^{\mathrm{mv}}(t) = \mathrm{NB}(t) + \mathrm{Mig}_T(t) + \sum_i \mathrm{mv}_i^{\mathrm{out}}(t) \tag{11}$$

where $N_T^{\mathrm{mv}}(t)$ is the total number of potential movers in the greater region. $\mathrm{NB}(t)$ is the net birth rate, and $\mathrm{Mig}_T(t)$ is the net migration rate to the greater region, both estimated exogenously from census data.

(iii) Allocation of movers to zones: Movers are distributed across residential zones using a logit model that accounts for zone-specific characteristics, such as rent prices, and accessibility to workplace. An area quality proxy (e.g. distance to center) can be also considered.

$$\mathrm{mv}_i^{\mathrm{in}}(t) = N_T^{\mathrm{mv}}(t) \frac{e^{V_i(t)}}{\sum_k e^{V_k}(t)} \tag{12}$$

where the systematic utility of zones is defined as follows:

$$V_i(t) = \beta_{\mathrm{Rent}} \overline{P}_i^{R,(\Delta t_{\mathrm{perc,Res}})}(t) + \beta_{\mathrm{Acc}} \overline{\mathrm{Acc}}_i^{(\Delta t_{\mathrm{perc,Res}})}(t) \tag{13}$$

$\overline{P}_i^{R,(\Delta t_{\mathrm{dec}})}(t)$ represents the monthly rent per square meter in zone i at timestep t, averaged over the decision time window $\Delta t_{\mathrm{perc,Res}}$. The rent is determined endogenously from the surface area per resident in each zone. This averaging captures information delay, smoothing fluctuations in rent over the specified time period, $\Delta t_{\mathrm{perc,Res}}$. $\overline{\mathrm{Acc}}_i^{(\Delta t_{\mathrm{perc,Res}})}(t)$ represents the average accessibility to employment from zone i, averaged over the same decision time window $\Delta t_{\mathrm{perc,Res}}$. This variable accounts for changes in accessibility over time, again reflecting information delay. β_{Rent} and β_{Acc} are parameters calibrated from observed data, representing the sensitivity of the utility to rent and accessibility, respectively.

Accessibility is measured using a Hansen-type indicator (Hansen, 1959), which quantifies the ease of reaching employment opportunities:

$$\mathrm{Acc}_i(t) = \sum_j A_j(t)\ e^{\beta_{\mathrm{TT}}^{\mathrm{Acc}} \mathrm{TT}_{ij}(t)} \tag{14}$$

where $A_j(t)$ is the number of jobs in zone j, $\mathrm{TT}_{ij}(t)$ is peak-hour travel time from zone i to j at timestep t, and $\beta_{\mathrm{TT}}^{\mathrm{Acc}}$ is a decay parameter reflecting sensitivity to travel time. The exponential decay function captures how accessibility declines with increasing travel time. Higher values of accessibility indicate greater access to employment opportunities within reasonable travel times.

In the allocation of potential movers, it is assumed that the choice of destination is not influenced by the location of the current domicile of movers.

The housing development sub-model simulates the construction of new dwellings. The decision to develop is based on the following factors: (i) housing demand, and (ii) availability of land for construction. Housing demand is defined in terms of the ratio between the current surface area per resident and the desired surface area per resident. The lower this ratio is compared to 1, the greater the need for new construction. Newly constructed housing becomes available after an externally defined construction time lag, denoted by $\Delta T^{\text{Cnst}}_{\text{House}}$. As new dwellings are developed, the total housing stock increases, thereby raising the surface area per resident. This, in turn, reduces the need for further development and also lowers rent levels. The construction of new housing units is constrained by land availability; if insufficient land is available, the scale of residential development is adjusted accordingly.

The output of the land-use module in each simulation step is the distribution of residential locations, which affects the trip generation and links the land-use module back to the transport module.

3 Illustrative example and results

In this section, the application of the proposed model is showcased using an illustrative example. The example considers three discrete spatial locations, each characterised by specific attributes such as population, socio-demographics, rental prices, transport infrastructure developments, job opportunities, centrality, and distances to other zones.

- Zone 1 represents a high-density urban area with higher residential rent prices compared to other zones. It is centrally located and hosts the majority of job opportunities.
- Zone 3, by contrast, is a less urbanised area with lower population density, lower rents, fewer job opportunities, and greater distances and travel times to other zones.

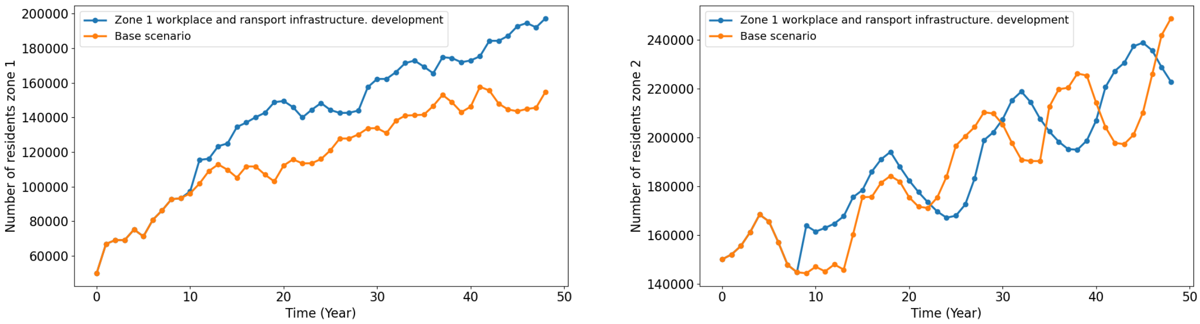
- Zone 2 is a semi-urbanised area situated between zone 1 and zone 3, offering more job opportunities and shorter travel times to zone 1 compared to zone 3.

The region assumes an exogenous annual immigration inflow rate of 1%, and an average household size of 2 person. Accessibility to workplaces is quantified using a utility-based measure for each residential zone. Number of job opportunities across spatial locations serve as a metric for zone attractiveness in trip distribution. The capacity of travel infrastructure (roads and public transport) are adjusted accordingly based on the travel demand and existing capacities. The rental prices are determined endogenously based on housing supply and demand dynamics. In the residential relocation sub-model, the logit model incorporates parameters $\beta_{\text{acc}} = 1$ and $\beta_{\text{rent/inc}} = -0.6$ to capture the effects of accessibility and rent-to-income ratio on relocation decisions. The system is simulated over a 50-year time horizon with annual time-steps.

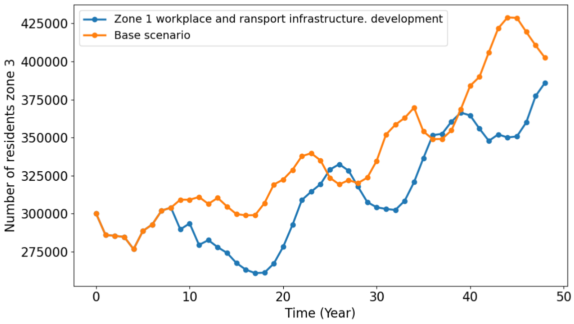
The system's behaviour under various policy scenarios is evaluated. Policy instruments can target transportation, such as new public transport infrastructure, fare adjustments, changes in road capacity, road charges, fuel costs, and parking fees. Alternatively, they can involve land-use measures, such as increasing the number of jobs in a zone, implementing development controls, and applying land-use charges, or a combination of both. As an example, the impact of a policy combining workplace development and transport infrastructure improvements in zone 1 at time-step 8 of the simulation is illustrated. Figure 6 shows the resident population across the three zones, with the number of residents under a base scenario with no external policies (orange line) provided as a benchmark for comparison.

Under the development scenario, zone 1 experiences a substantial population increase compared to the base scenario, highlighting the significant role of improved accessibility and job opportunities in attracting residents. From the model results, we observe a decrease in average public transport commute times of zone 1 residents from 24 minutes to 15 minutes, and higher share of public transport commute trips (from 33% to 48%) after the public transport infrastructure expansions connecting zone 1. Zone 2 also shows moderate population growth, benefiting from spillover effects due to its proximity to zone 1. Conversely, zone 3 sees a population decline in the development scenario, particularly after year 10, as residents relocate to zones offering better accessibility, employment prospects, with lower residential rents. These trends emphasise the trade-offs residents make between accessibility, housing affordability, and other factors when choosing their residential locations.

Figure 6: Population dynamics in the region under the workplace and transport development scenario in Zone 1 at timestep 8.



(a) Resident population of Zone 1 (b) Resident population of Zone 2

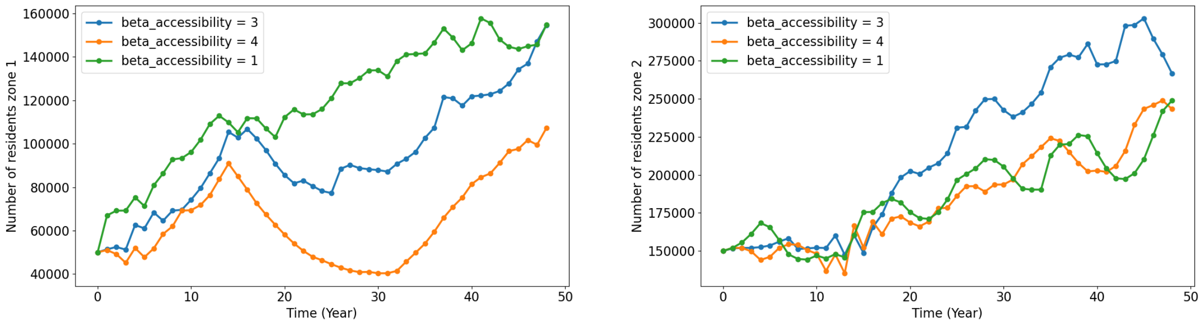


(c) Resident population of Zone 3

In Figure 7 sensitivity of residents to their accessibility to workplace is tested in three scenarios. Sensitivity analysis tests the robustness of the model. It determines whether the model results change in ways important to the purpose of the study when assumptions are varied over the plausible range. As the importance of accessibility to workplaces increases for residents, commute time becomes a more significant factor in their residential location decisions, often outweighing the utility of more affordable rent prices. There is a always a trade-off between more affordable rent prices and accessibility to workplace, with neither factor alone determining residential choice. In scenarios with high sensitivity to accessibility, residents show a clear aversion to the more distant zone 1 and a strong preference for the central zone 3, despite its higher rental costs compared to farther zones. This suggests that proximity to workplaces can outweigh rent prices for many individuals in such scenarios with the assumed parameters for the illustrated example.

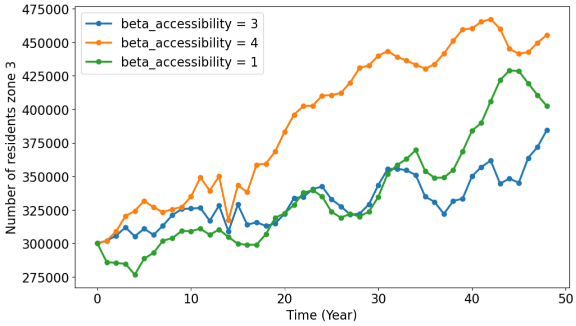
The model has been tested to assess the validity of the framework and ensure its robustness. Examples of tests conducted include extreme condition tests, dimensional consistency

Figure 7: Effect of sensitivity of residents to accessibility to workplace on residential location choice.



(a) Resident population of zone 1

(b) Resident population of zone 2



(c) Resident population of zone 3

checks, and sensitivity analyses on different model parameters.

4 Conclusions

This paper combines transport and land-use models within the same framework, simultaneously simulating the modules over a time period of multiple years with dynamic simulation. The framework explicitly accounts for the interactions and feedback between transport and land-use systems. It is developed based on the principles of System Dynamics modelling (Sterman, 2000), leveraging transport manuals, econometric, and behavioural models for quantification. The framework offers key advantages: (i) an integrated design that allows for simultaneous simulation, (ii) independence from the concept of urban equilibrium, with the state of the urban system dynamically derived and accommodating different time lags within the system, (iii) the development path over time is captured with dynamic modelling, (iv) a modular structure that provides flexibility for incorporating new features and aspects as needed by the analyst, (v) reproducible results, (vi) computationally quick (simulations of a 50-year time horizon completed in under a minute), and (vii) functionality as a decision-support tool capable of evaluating the combined effects of multiple policies over time in a manner that is accessible to decision-makers. Additionally, the framework allows the analyst to define the start and end points, as well as the levels of any policy instrument.

This work offers avenues for further extensions and improvements, paving the way for future research. Currently, car ownership is not included in the specifications; incorporating this factor into travel mode choice models could enhance their realism. The workplace model is assumed to be exogenous. Future studies could focus on endogenising workplace relocation dynamics within the framework. Additionally, other dimensions of choice complexity could be explored. For instance, while renting is currently assumed as the sole means to meet housing needs, incorporating the option of buying could provide a more comprehensive representation of residential demand. The interplay between renting and buying decisions could then be analysed in greater detail. An empirical application of the proposed framework to Luxembourg is undertaken. Some results of the Luxembourg case-study will be presented in the STRC conference. This investigation involve calibrating the model parameters to reproduce the observed behaviour of the country and testing various scenarios specific to Luxembourg as a case study. The current model specifications are deterministic. Incorporating uncertainty and exploring probabilistic specifications is a promising direction for future research. Additionally, incorporating factors such as the time value of money and inflation rates into the model could enhance its applicability and realism.

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