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Research Article

Trade-offs between sustainable development goals in systems of cities

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ABSTRACT

Sustainable Development Goals are intrinsically competing, and their embedding into urban systems furthermore emphasises such compromises. When observed at the scale of systems of cities, such concern is considered as a series of innovations that challenges the adaptive capacity of urban systems. The spatial complexity, the non-optimal nature of such systems, and the multi-objective aspects of their agents, are among the reasons that raise difficulties when trying to adjust local policies through promoting innovation in order to satisfy at least a couple of SDGs simultaneously. As we lack enough empirical evidence, we propose in this paper to use a stylised simulation model for systems of cities, focused on innovation diffusion and population dynamics, to show how trade-offs may operate at such a scale. We proceed in particular to a bi-objective optimisation of emissions and innovation utilities, and show that no single urban optimum exists, but a diversity of regimes forming a compromise between the two objectives.

1. Introduction

1.1. Urban systems and urban sustainability

The 17 Sustainable Development Goals that were defined by the United Nations in 2015 (Nations, 2015) are challenging the adaptation capability of many cities in the world. As they host a growing proportion of the world population and are responsible for a large part of greenhouse gas emissions (Christen, 2014), cities are at the core of environmental transition policies (Romero-Lankao & Dodman, 2011). Indeed, cities are explicitly mentioned in SDG 11 (Nations, 2015): “Make cities and human settlements inclusive, safe, resilient, and sustainable”. This citation demonstrates that many other SDGs involving a diversity of urban issues and stakeholders are already embedded in that specific goal (Vaidya & Chatterji, 2020).

In the ongoing adaptive process of the environmental transition, cities are not isolated. They have been engaged for long in a co-opetition process for attracting population and economic activities that have created many interdependencies in their evolution leading to interpret cities as “systems within systems of cities” (Berry, 1964). These systems of cities are an almost universal form of spatial organization of societies to inhabit the earth space. This organization has proven to be very sustainable for several millennia, because it offered a way to continuously adapt the political, economic and technological innovations that societies imagined over the

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centuries (Pumain, 2020). That remarkable ability to resilience through self-renewal has expanded all over the world up to the point that the largest metropolises may have now become "global rulers" (Glaeser et al., 2020). However, for the last few decades urban systems seem to be threatened by excessive emissions and overexploitation of the planet's energy and material resources (Kourtit et al., 2020; Nijkamp & Perrels, 2014). While demographic and economic growth have supported and accelerated the development of urbanization and the proliferation of systems of cities for two centuries, they are now accused of being the cause of climate change problems and the rise of social inequalities (Davis, 2006; Glaeser et al., 2009). It seems that the excessive mobility associated with the fragmentation of the value chains of globalized production has progressively decoupled urban expansion from the proper management of planetary resources (Rozenblat, 2018). It is unlikely that the technological solutions that are provided under the label of "smart cities" could easily solve these problems (Caragliu et al., 2011; Kourtit et al., 2020), especially because of the huge diversity of cities internal layouts and their already established networks operating internal and external interactions (Caruso et al., 2022).

1.2. Investigating transitions towards sustainability

Regarding the adaptation process to SDGs, recent research follows two main lines, involving theoretical and empirical investigations. On the theoretical side, the last three decades have produced a huge literature, mainly oriented toward assessing the relationship between gas emissions and GDP over time. The environmental Kuznets curve (EKC) hypothesis proposes that there is an inverted U-shape relation between environmental degradation and income per capita (Dinda, 2004; Stern, 2004). This has been taken to imply that economic growth will eventually redress the environmental impacts observed from the early stages of economic development. Implications for innovation policies remain unclear, as some authors suggest to rely on existing technologies to reduce emissions (Brisbois, 2022). Furthermore, difficulties linked with conceptual definitions and indicators measurements, although helping to clarify the issue, have not led to a complete consensus about the robustness of that hypothesis (Harbaugh et al., 2002). Most tests regarding that hypothesis have been made at a macrogeographic level and compare national statistical evolutions. The observations made at city level are more recent and fragmented. Empirical investigations about SDGs in cities still lack of well-established and comparable sources of information. Thus they follow a diversity of directions: either identifying relevant indicators for benchmarking and monitoring the improvement process (Giles-Corti et al., 2020), or measuring their variations according to city size (Laituri et al., 2021) and according to specific practices and specific national contexts, such as for example inclusivity in South Africa (Mudau et al., 2020), road safety in India (Mohan et al., 2021), contextualisation of goals in Germany (Koch & Krellenberg, 2018), or the relationship between carbon emissions and polycentric structures in China (Zhu et al., 2022, p. 185).

Alongside the many localised investigations, we believe that abstract modelling, which distances itself from the diversity of cities, their cultures and subjective sensitivities, can help as a first step to discern some of the possible ways of managing urban dynamics (Pumain & Reuillon, 2017). A good knowledge of urban systems dynamics is required to prepare possible interventions in such systems because of their intrinsic complexity (Reggiani et al., 2021). Systems of cities are characterised by co-evolutionary processes with non-linear dynamics far from equilibrium, which makes forecasting attempts particularly difficult (Raimbault, 2020c). By integrating stylised facts from a large number of observations into simulation models, it is possible to list the most probable paths of their dynamics and to support reflection on possible evolution, without proposing a priori a horizon that would be more desirable than another. Indeed, we have often found that the diversity of cities, in size and function, is an important component of the adaptive dynamics of systems of cities (Pumain, 2021). The search for an optimum that would value adaptation to a standard or to the situation of the moment would necessarily be doomed to failure. Moreover, a specific attention should be paid to temporal scales: a recent attempt at modeling urban growth with empirical observations of daily mobility rediscovers that not only "strong social interactions but also long-term memory effects" are major principles for capturing urban dynamics (Xu et al., 2021).

1.3. Conflicting sustainability objectives

The concept of urban optima, in the sense of optimising certain dimensions of urban systems, has been considered from diverse perspectives. It is often conceived within the economic paradigm of equilibrium (Glaeser, 2008). In most cases, there does not seem to be clear patterns, neither empirical nor theoretical, of possible simple optimisation of single objectives by urban systems. Some results in urban economics regarding an optimal city size require to consider a city in a closed system, what is unreasonable from a realistic perspective (Singell, 1974). Studies of an optimal urban population density are restricted to economic criteria of wage and productivity (Su et al., 2017). The sustainability of urban forms for CO2 emissions requires considering complex indicators of urban form (Le Néchet, 2012). Similarly, no universal rule seems to exist for the scaling of emissions with city size (Gudipudi et al., 2019). In terms of pollution, empirical results across different urban systems suggest no fixed relationship between city size and emission of pollutants (Han et al., 2016). Altogether, this converges with the idea of multiple agents optimising multiple dimensions at different scales (Pumain, 2008), and therefore no empirical support for simple "urban optima".

Sustainable Development Goals (SDGs) are characterised in a similar way by compromises between different dimensions. Urban sustainability, in the sense of the urban aspect of environmental issues (Finco & Nijkamp, 2001), has thus to be understood as trade-offs between multiple objectives (Viguié & Hallegatte, 2012). This aspect occurs within subsystems themselves, such as in the case of designing transport networks (Sharma & Mathew, 2011). Planning and policies must in that context account for such competing objectives (Caparros-Midwood et al., 2015).

1.4. Proposed approach

We propose in this paper to study trade-offs between different SDGs in systems of cities. Our research question couples the two streams of literature reviewed above: we inquire how urban dynamics stylised modeling can be applied to the exploration of conflicting SDGs dimensions. We consider systems of cities at the macroscopic scale, and more particularly the dynamics of innovation diffusion and population growth. Using a stylised model for such urban dynamics, we apply a bi-objective optimisation genetic algorithm, to explore how trade-offs can occur in such systems.

The rest of this paper is organised as follows: we first recall the assumptions of the system of cities model applied; we then describe results of its optimisation on proxies for two SDGs (innovation utility and emissions); we finally discuss theoretical implications of these results and how further work could include empirical components.

2. Urban system model

We work with a stylised model for the dynamics of urban systems at the macroscopic scale (i.e. a country or a continent or any integrated region of the world). This model is based on innovation diffusion dynamics and their impact on population growth. It was first formulated by Favaro and Pumain (2011), within the context of an evolutionary urban theory (Pumain, 1997). A similar agent-based model was used to explore assumptions on the emergence of systems of cities themselves (Schmitt et al., 2015). A modified version was described by Raimbault (2020b) as an urban evolution model, including an urban genome shared and mutated across cities. As this particular version can furthermore be setup on stylised systems of cities, we use it in our multi-objective optimisation approach. We give below a detailed description of model setup and dynamics.

2.1. Model setup

The simulated urban system is composed by cities, which location in the geographical space and number are fixed in time. They are characterised at each time step by their population $P_i(t)$ and by adoption rates by their populations for different innovations, what corresponds to an "urban genome" as a matrix $\delta_{i,c}(t)$ with c being the index for successive innovations.

We work on synthetic systems of cities, which are randomly generated given some fixed macro characteristics. This approach allows controlling for example for the role of space, and disentangling intrinsic model dynamics from geographical contingencies (Raimbault et al., 2019). In our case, as emission indicator is linked to inter-city flows, strongly dependent on the geography, averaging over several synthetic systems of cities will thus provide robust results.

Synthetic systems of cities are generated with random locations, an initial rank-size hierarchy which can be tuned (otherwise fixed to a default value of 1, to mirror a Zipf law distribution for city size (Cottineau, 2017)), and a number of 30 cities. The largest city has initially a population of 100,000 and the model is run for 50 time steps. These values correspond to an order of magnitude of a regional or national system of cities on a period of one or two centuries, which is the correct application context for this model (Favaro & Pumain, 2011). Such a setup is furthermore usual for synthetic cases in this family of models, such as for the SimpopNet model systematic exploration (Raimbault, 2020c), for a co-evolution model between cities and transportation networks (Raimbault, 2021), and for this specific version of the innovation diffusion model (Raimbault, 2020b).

2.2. Model dynamics

Starting from the initial state, the model updates population and innovation step by step. At each time step (of an order of magnitude of a few years - the effects are observed on long time scales), the following procedure is used:

1. Innovations are diffused between cities using a spatial interaction model - innovations with a higher utility will diffuse more quickly and obtain higher adoption shares (Hagerstrand, 1968); innovation shares are updated, with $p_{c,i,t} = \delta_{c,i,t} \cdot \frac{P_i(t)}{\sum_k P_k(t)}$ the city-level share of adoption, u_c the utility of innovation c, and d_I the spatial interaction range for innovation diffusion, following

$$\delta_{c,i,t} = \frac{\sum_j p_{c,j,t-1}^{\frac{1}{u_c}} \cdot \exp\left(-\frac{d_{ij}}{d_I}\right)}{\sum_c \sum_j p_{c,j,t-1}^{\frac{1}{u_c}} \cdot \exp\left(-\frac{d_{ij}}{d_I}\right)} \tag{1}$$

2. Populations are updated following an other spatial interaction model (Raimbault, 2020a), with a population growth advantage for cities being more innovative; more precisely, new populations are computed as

$$P_i(t) - P_i(t-1) = w_I \cdot \sum_j \frac{V_{ij}}{< V_{ij} >} \tag{2}$$

where the spatial interaction potential for population growth is given by

$$V_{ij} = \frac{P_i(t-1)\cdot P_j(t-1)}{\left(\sum_k P_k(t-1)\right)^2}\cdot \exp\left(-\frac{d_{ij}}{d_G}\cdot \prod_c \delta_{c,i,t}^{\varphi_{c,t}}\right) \tag{3}$$

with $\varphi_{c,t} = \sum_i \delta_{i,c,t}\cdot P_i(t-1)/\sum_{i,c}\delta_{i,c,t}\cdot P_i(t-1)$ macroscopic adoption rate, w_I population growth rate parameter, d_G spatial interaction range for population growth, and d_{ij} the geographical distance between cities i, j;

3. New innovations may be invented in cities, following a probability determined by a mutation rate and by population with a given hierarchy across cities as

$$p = \beta\cdot (P_i(t)/\max_k P_k(t))^{\alpha_I} \tag{4}$$

with β intrinsic innovation rate and α_I innovation hierarchy; this follows the empirical fact of superlinear innovation scaling (Arbesman et al., 2009);

4. If a new innovation emerges, it has an initial penetration share fixed by one parameter r_0, and a utility drawn from a random distribution (normal or log-normal law, with the type of law being also a model parameter), with a fixed standard deviation σ and an average corresponding to the current empirical average of existing innovation utilities.

The last assumption regarding the utility of new innovations allows capturing some kind of "creative destruction" (Diamond Jr, 2006), in particular through the skewed distribution of the log-normal, which will lead to a higher frequency of better innovations replacing older ones through diffusion. With the normal law parametrisation, utilities will still increase in average due to the selection through diffusion, but less faster.

2.3. Model parameters

The model parameters left free for optimisation are.

1. Spatial interaction range for innovation diffusion d_I
2. Spatial interaction range for population growth d_G
3. Mutation (innovation) rate β
4. Level of hierarchy to select cities inventing a new innovation (scaling of innovations with regard to urban size) α_I
5. Rate of early adopters r_0
6. Standard-deviation of new innovation utilities σ
7. Type of distribution for new innovation utilities.

Some parameters can be parametrised from real data in a rather straightforward way, such as spatial interaction ranges by fitting spatial interaction models on appropriate data for example (Fotheringham & O'Kelly, 1989), or the level of hierarchy for new innovations by fitting urban scaling laws (Pumain et al., 2006). Other parameters such as innovation rate or the distribution of innovation utilities correspond to a more abstract formulation which can not directly be linked to real-world proxies (for example, innovations compete along a single dimension). Furthermore, some parameters can be linked to potential policies while others can difficultly be acted upon. We choose thus to work with most parameters free to maximise the degrees of freedom explored by the optimisation algorithms, in some sense to explore a broader set of scenarios for urban systems.

2.4. Optimisation objectives

We consider the "innovation" SDG (goal 9) and the "climate" SDG (goal 14) as conflicting objectives. We can expect that a higher economic activity linked to more intensive innovative activities will increase endogenous emissions, but also transport emissions between urban areas, generated by economic and transport flows. Our indicator for transport emissions remains a rough proxy capturing potential mobility intensity, which does not include possible effect of innovations reducing transport emissions. We assume that such activity however reflects a significant component of mobility emissions. Indeed, empirical evidence does not suggest globally a simultaneous reduction of emissions through innovation (Chen & Lee, 2020). A potential decoupling of economic activity and emissions remains also still difficult to observe (Haberl et al., 2020). For these reasons, we can expect a compromise between these two dimensions. The effective existence of a trade-off in synthetic urban dynamics generated by the model remains in that context an hypothesis, which will be checked during the optimisation stage (here "optimisation" means trying to minimise simultaneously different stylised output indicators of the model).

We consider therefore the two following objectives for model optimisation:

1. Aggregated total utility during model dynamics, computed over time and across cities, with shares of each innovations, as

$$U = \sum_{t,i,c} \delta_{t,i,c} \cdot \frac{P_i(t)}{P_t} \cdot u_c \tag{5}$$

where P_t is the total population;

2. Total emissions due to transport flows between cities, computed as cumulative population gravity flows; this indicator can be understood as some index of "mobility intensity" and used as a proxy for emissions; it is computed as

$$E = \sum_{t,i,j} \frac{P_i(t)P_j(t)}{P_t^2} \cdot \exp\left(-d_{ij}/d_G\right) \tag{6}$$

Note that in this abstract model and with the proxy used, "emissions" captures any production or process contributing to GHG emissions or to resource exhaustion linked to urban growth. More detailed indicators parametrised with empirical data remain to be explored.

3. Results

3.1. Implementation

The model is implemented in scala for performance purposes, using matrix operations to update innovation shares and populations. Source code and simulation results are available on the open git repository of the project at https://github.com/JusteRaimbault/SDGTradeoffs.

Model optimisation is achieved by integrating the model into the OpenMOLE platform (Reuillon et al., 2013). This free and open source software facilitates model embedding into a workflow system, distribution of computations into high-performance computing infrastructures, and provides a simple access to state-of-the-art model validation methods.

3.2. Bi-objective optimisation

We investigate trade-offs between total innovation utility and emissions, by optimising the model using a bi-objective heuristic with free parameters and indicators detailed above. We use a NSGA2 optimisation algorithm, provided by OpenMOLE, with a population of

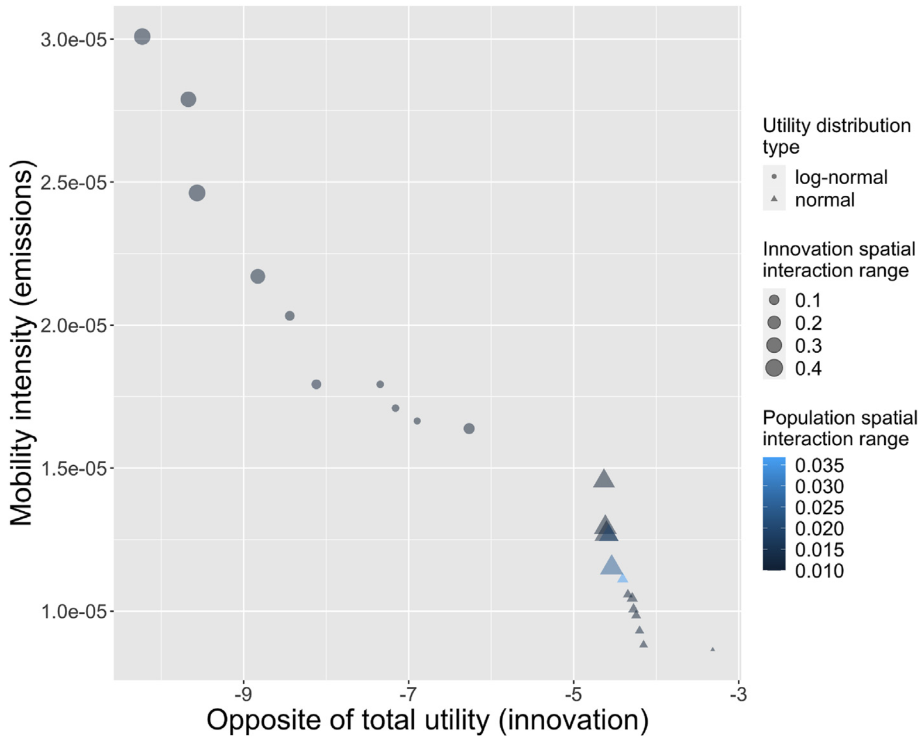

Fig. 1. Pareto front between the opposite of average utility (innovation) and mobility intensity index (emissions). Point colour gives population spatial interaction range; point size innovation diffusion range; and point shape the utility distribution. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

100 individuals, for 10,000 generations. The genetic algorithm proceeds iteratively, by progressively selecting an optimal population of individuals (parameter points), constructed from the previous generation of optimal individuals. We observe convergence when the hypervolume of the Pareto front becomes steady, what we observed in practice with this total number of runs.

We show optimisation results, as the final algorithm population, in Fig. 1. We indeed find a broad Pareto front, confirming the existence of a trade-off in such urban dynamics driven by innovation diffusion. We note two parts of the Pareto front, with fat-tailed distributions for utility distribution (log-normal) giving the upper part of the front corresponding to situations with a higher utility but which are more emission intensive. Within this subfront, population spatial interactions are rather local, while a more local innovation diffusion yields less emitting configurations. A similar aspect is observed for the normal distribution subfront, with a U-shaped value of population spatial interactions when going through the front: a more integrated system in terms of population migration produces by itself an intermediate compromise.

3.3. Conditional optimisation

We now turn to experiments which could potentially provide policy insights. We run the same optimisation as before, but changing the initial population hierarchy of cities. To put it simply, we investigate how trade-offs change in different hypothetical systems of cities, ranging from highly hierarchical (Zipf exponent of 1.5) to a more balanced system (exponent of 0.5). We expect to obtain different Pareto fronts, for different values of a hierarchy index, which corresponds to the slope of the initial Zipf law.

We show results in Fig. 2. We find that the higher the hierarchical inequalities, the less flat the front. Overall, the less hierarchical system dominates the others (but this comparison remains limited as total population is different across systems). Furthermore, the extent of the Pareto front is the smallest with the less unequal hierarchy, meaning that this system is indeed closer to some global optimum and exhibits less compromises.

We finally show in Fig. 3 a similar conditional optimisation, run by changing the fixed value of innovation hierarchy. This corresponds in terms of policies, to either letting innovation aggregate into larger metropolises (scaling with a high exponent value (Pumain et al., 2006)), or regulating and providing incentives to enhance innovation into smaller and medium-sized cities. We also find that balanced policies provides a more optimal front (they can be compared in this case). Furthermore, this lowest hierarchy corresponds to much higher absolute values of total utility, going against the narrative of a higher value innovation produced by large cities only. Points for the two other fronts are rather close, corresponding to a lower sensitivity when the scaling exponent is larger than one.

4. Discussion

We have shown, in a stylised model of urban population and innovation dynamics, that trade-offs between transport emissions and

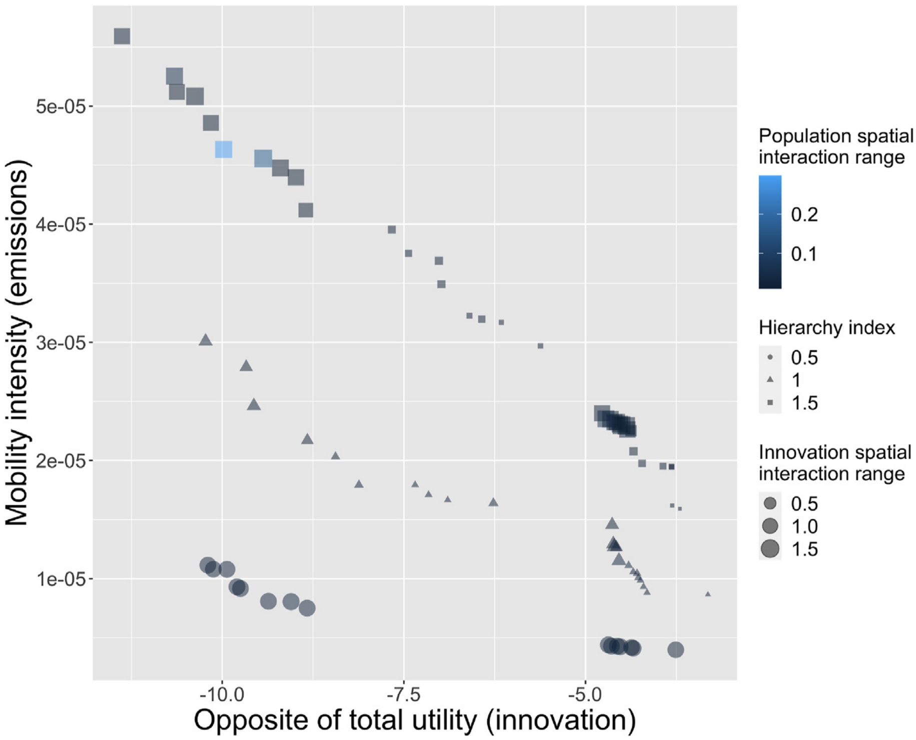

Fig. 2. Pareto fronts, with initial population hierarchy index fixed at different values (point shape).

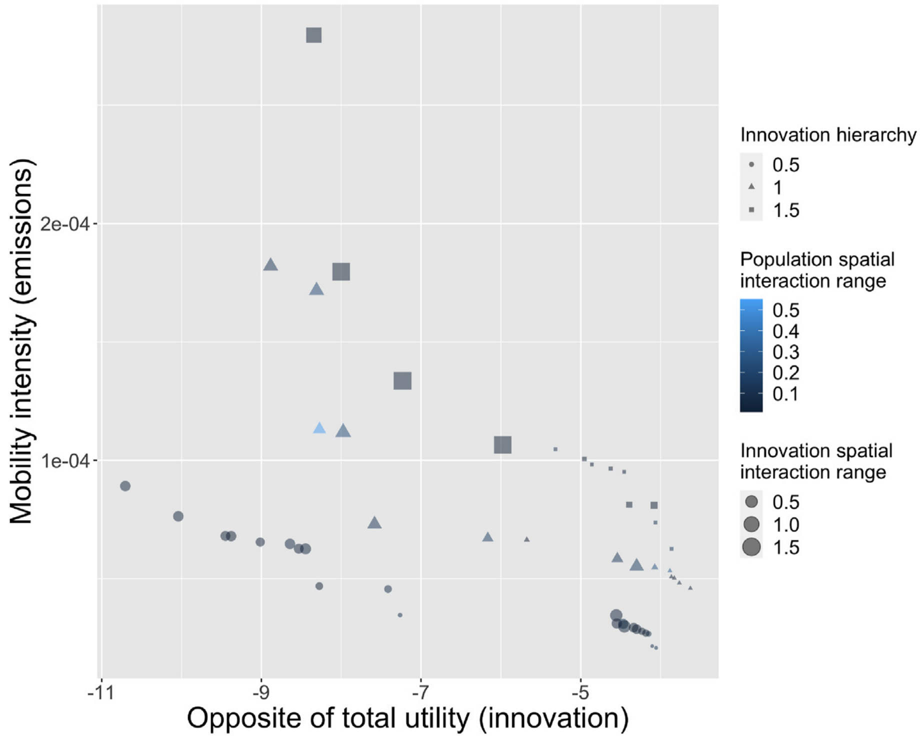

Fig. 3. Pareto fronts, with innovation hierarchy fixed at different values (point shape).

total innovation utility emerge from model dynamics. This has theoretical implications, confirming the general non-optimising nature of urban systems and the predominance of trade-offs across different urban dimensions. Our results from conditional optimisation suggest that less hierarchical systems, both regarding initial population hierarchy and innovation hierarchy, provide more optimal Pareto fronts. This could have implications for policies such as innovation incentives, to avoid a too strong concentration into larger cities. More empirical investigations remain however needed to confirm these conclusions.

Extending this theoretical and stylised work towards more empirical and data-grounded applications raises several issues. First, how to quantify spatial proxies for innovation, to either parametrise the initial configuration, or to calibrate model trajectories in terms of innovation diffusion, remains a difficult question. The use of patent data provides such insights (Griliches, 2007), but the lack of harmonised and spatialised open patent database limits this perspective. Some initiatives are currently working towards this goal (Bergeaud and Verluise, 2021). Furthermore, more realistic indicators for emissions, both transport and endogenous ones, would be also needed, for example by estimating them through a link with existing emissions databases such as EDGAR (Olivier et al., 1994).

Adding supplementary optimisation dimensions, to include further SDGs in simulated dynamics, is also an important future model development. For example, there is empirical evidence of a relationship between wage inequalities and city size (Shutters et al., 2022), what implies different levels of inequality for different hierarchies of an urban system. This dimension corresponds to one additional SDG. Being able to couple this model with additional layers would thus allow including more goals, and investigate multi-dimensional trade-offs. Simulation models from the same modeling stream are good candidates for this, such as the Marius model to include the GDP of cities (Cottineau et al., 2015), or a model including the evolution of transport infrastructure (Raimbault, 2021). Coupling such simulation models is however not straightforward, and necessitates preliminary model benchmarking such as done by Raimbault et al. (2020) to then build a multi-modeling common framework. Also, including further objectives would imply changing the optimisation algorithm to use many-objective optimisation instead of multi-objective optimisation, by switching to the NSGA3 algorithm for example (Deb & Jain, 2013).

Finally, several model limitations would require investigation. The urban genome is unidimensional, what means that only one technological domain (or function) is considered, and abstract in the model. Linked to the remark above on transport technology innovation potentially reducing emissions, a multi-dimensional extension of the model would allow to include such aspects. An other aspect limiting the goals which can be included is the single macroscopic scale, and an extension into a multi-scale urban dynamics model would allow taking into account more aspects linked to social dynamics.

To conclude, we have provided a first stylised insight into trade-offs between SDGs in systems of cities at the macroscopic scale, which can be applied from a theoretical viewpoint to validate or invalidate urban theories, and be used as a basis towards more practical applications to sustainable long-term territorial policies (Rozenblat & Pumain, 2018).

Declaration of competing interest

We do not have any conflicts of interest to disclose.

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