From Smart to Cognitive Cities: Learning for Sustainability

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Abstract

Smart city development is a strategy to address problems caused by rapid urbanization and socio-economic challenges. While the notion of a 'smart' city is ubiquitous, this paper argues that what is needed is not a city where managerial responsibilities have been handed over to ICT, but rather to conceptualise the city as an ecosystem. This perspective posits the city as a complex adaptive system, a cognitive city, which adaptively learns via urban planners and managers. With reference to the Covid-19 pandemic and the UK response, we recognise various constraints to human judgement and decision making under complex conditions, and advocate the contribution of *in silico* simulations and controlled experiments to test future threats and response scenarios. These facilitate identifying unsustainable future trajectories and the development of alternative strategic opportunities to foster building systemic resilience in anticipating future shocks, and that doing so is an ethical necessity to conserve the viability of future city systems.

[154] → need to trim 4 words.

1. Introduction

In their most recent report[1], the UK's National Audit Office (NAO) observed that the global Covid-19 pandemic had "stress-tested the government's ability to deal with unforeseen events" and emphasised that the government needed a systematic plan for dealing with emergencies, and the ability to learn at speed (National Audit Office, 2021). The recent pandemic highlights but one example of large scale and rapidly evolving situations that governments, managers and planners in cities must respond to. Given the even more conservative scenarios in recent Intergovernmental Panel on Climate Change (IPCC)reports, the impacts of climate change will be nothing less than critical, large scale, dynamic and probably irreversible. The sole advantage the government, along with others with governance and planning responsibility involving large numbers of people's welfare, such as city managers and planners, have with respect to climate change which they did not have with the pandemic, is that we have been very much aware of the former and still do have time to plan for it. Nevertheless, how the government responded to the pandemic, both during and after the crisis, serves as an illustration of what is required in managing for emergencies.

Despite various definitions, the smart city is still a fuzzy concept with an over-reliance of technological interventions (Israilidis, Odusanya and Mazhar, 2019). In this paper, we locate the discussion on the city as a spatial dynamic assemblage of people, governance, technology, economics, and nature and interrogate the notion of the 'smart' city and its goodness of fit to respond to challenges that are foreseen, such as climate change, and those which catch us by surprise, such as a global pandemic. In particular, we problematise the notion of smart cities as those which simply hand over managerial responsibility and functions to computer assisted technology, and develop the argument that, conceptually and practically, we need to move beyond this notion to construe urban conurbations as ecosystems. This shift in emphasis explicitly recognises that cities converge organisms and inorganic materials within the same structurally coupled spatio-temporal domain; it enables us to scaffold the argument in favour of positing cities as complex adaptive systems (Portugali, 2000), much in the way that we conceive of ecosystems as dynamic and complex.

In making the case for this qualitative shift, we propose that rather than valorising smart cities, we need to hold the bar higher and pitch instead for cognitive cities. In doing so, we propose that the city, as a complex adaptive system, is itself structurally coupled with its larger environment, its niche, with which it must successfully conserve its organisation in order to persist and endure over time. It is only by doing so, by expanding our conceptual framework, that we can begin to systematically plan for emergencies, both known and unknown, and to lock in functional redundancy for cities as systems to absorb shocks without changing state conditions (e.g., Allan & Bryant, 2014).

We conclude this brief paper by exploring the applications to which *in silico* experiments and simulations can be recruited for stress testing the city system's adaptive capacities, and to enhance the scope for strategic planning to anticipate and build in systemic resilience for future shocks. Therefore, this can help realise the ambition of United Nations (UN) Sustainable Development Goal 11: Sustainable Cities and Communities which calls for making cities and human settlements inclusive, safe, resilient and sustainable.

1 https://www.theguardian.com/world/2021/may/19/covid-laid-bare-existing-weaknesses-in-uk-government-says-nao Accessed: May 19, 2021

2. React, Respond, Adapt: Learning from the Future

Urban migration and settlement dynamics have long been phenomena of research interest among geographers, urban planners, and sociologists. With increasing concerns about human impacts on local and global ecosystems and the emergence of sustainability and sustainable development as determinants of policy and regulatory frameworks, urban configurations have attracted further interest among researchers in the evaluation of how such conurbations are, and can be better, positioned relative to these frameworks. As cities have increased in both size and complexity, some have become classified as 'global' cities, a term which describes their position as hubs within a transnational network, linking economic and social transactions with other cities across the world (Cosgrove, 2017). As with all complex systems, bounding discrete limit points which demarcate the boundaries of one system from the beginning of another is arbitrary, and this applies not only to so-called global cities, but also to urban conurbations with rich and multi-dimensional linkages to peri-urban and rural hinterlands. Rather than thinking of cities as places then, it becomes more meaningful to conceptualise cities as regions of intensification that converge land use and cover, and population densities, along with their emergent infrastructures.

Consequently, the city and its complex web of stocks and flows is more appropriately described as a metabolic system, an ecosystemic configuration converging humans and inorganic materials (Anderson & Elmqvist, 2012). Cities are ecosystems which not only favour humans, but also support a vast array of non-human organisms, from rats and insects, to urbanised wildlife, and bacteria and virus colonies moving along a multiplicity of nutrient and disease vectors. That is to say, in cities, as humans we are entangled in the multi-scalar and complex networks of relations with technology, non-human organisms, and inorganic materials. The behaviour of a system is determined by its structure, its feedback loops and the flows and stocks and the emergent non-linearities of its interacting components.

Conceptualising cities as complex systems is an approach that is increasingly being endorsed, along with the use of agent-based modelling methods to interrogate a range of phenomena, from the structure of communities to the potential failure risk of power systems (Thakuriah, Tilahun, & Zellner, 2017). Modelling cities as adaptive favours a shift towards preparing to respond to future challenges, rather than reacting to them once they are under way; this exposes a significant quandary for those attempting to run controlled experiments in scenario forecasting to anticipate what is more probable and distinguish this from what is less probable, and to incorporate data relevant to exploring predicted outcomes and response options. To effectively run simulations anticipating future scenarios modellers must not only balance events that are high impact and high probability, but also those that are high impact with a low or even unknown probability of occurring (uncertainty and surprise). All these judgements take place as cognitive acts and are effectively expressions of the mental models recruited by the systems analysts, and herein lies the challenge. If the analyst's mental model excludes some scenarios, this becomes a modelling blind spot: one does not know what one does not know.

3. Learning to Learn in and from Complex Conditions

The challenge with complexity is that it compels us to realise that "[w]e are all passengers on an aircraft we must not only fly but redesign in flight" (Sterman, 2000: 4), and human cognition struggles with complex recursive operations. There are a number of well documented reasons for this, which have been described in terms of flawed cognitive models/ mental maps. As Forrester notes "[t]he mental model is fuzzy. It is incomplete. It is imprecisely stated. Furthermore, within one individual, a mental model changes with time and even during the flow of a single conversation" (1971: np). But this is not a problem that is easily resolved through assembling a team of modellers. One's mental model is, on one hand, individual and unique, but on the other, is socially structured and determined, in part due to the cognitive architecture and shared heuristics with which we as humans conserve our autonomy as a species. Indeed, an argument can be made that posits the Anthropocene as a limit point to both human progress and to human cognition exposing the folly of notions of infinite economic growth and ignoring complexity in favour of simple linear models (Mitchell, Lemon, & Lambrechts, 2020).

In addition to such limitations associated with mental models, humans are also notoriously poor at making decisions and judgements that are free of biases (Hogarth, 1981). Moreover, we struggle to understand causal relations (Einhorn & Hogarth, 1986), and express a strong tendency to insist on the validity of initial judgements despite evidence to the contrary (Einhorn & Hogarth, 1978). The UK government's response to the global pandemic keenly illustrates this tendency. By the early part of 2020 when the pandemic was identified as a worldwide health crisis by the World Health Organisation (WHO), the UK had already been engaged in emergency health planning for a number of years (Lee, Phillips, Challen, & Goodacre, 2012). All planning scenarios to that point had however been based on the transmission models of the common flu, and despite a lack of evidence to support similarities in transmission vectors between the two viruses, the UK government responded to the new threat in the same ways as it had modelled its responses to a virus with which it was already familiar (Scally, Jacobson, & Abbasi, 2020). Responding to the wrong virus exemplifies how we tend to constrain responses to the novel by insisting on applying responses to which we are already familiar, even if there is no alignment between the two (Dörner, 1996). This response error, in conjunction with a series of politically driven economic strategies which weakened the UK's infrastructure and the health care system in particular, led to the UK finding itself unable to adequately respond to the novel emergent threat (Lee, English, Pankhania, & Morling, 2021).

There is a large and growing body of research into judgement and decision-making which repeatedly indicates the influence of a range of cognitive limitations. These include defensive routines, selective attention, inability to track time lags between causal chains, differences of spatial scales, and confirmation biases, along with a long list of heuristics (Kahneman & Tversky, 1979; Simon, 1990; Thorndike, 1920; Tversky & Kahneman, 2007). All of these occlude and distort the capacity for human cognition to deal effectively with complex and dynamic phenomena. This is not to propose that modelling should not be used to anticipate future scenarios. On the contrary, if anything, it actually makes the case for using scenario modelling and simulations to experiment with and to explore future and novel threats and to plan strategic adaptive responses. Indeed, modelling has been very successful in anticipating public health epidemics and impacts and appropriate response options (Thompson & Duintjer Tebbens, 2008). But what it *does* mean is that we need to be mindful that the models we rely on are limited by human cognition, the ways that we make sense of the world and deal with complexity, and to factor that into the learning processes. We also need to recognise the potential of such models to generate unforeseen and or unforeseeable futures rather than testing how likely our own (diverse) perceptions of that future might be. How can we learn from those futures to make informed judgements about their likelihood, potential responses and what capital needs to be held in reserve (redundant) to respond to, or avoid, them?

4. Cognitive Cities: Adaptation as Learning

Given the foregoing, how can city managers and planners exploit the advantages of using *in silico* computational scenario planning while also avoiding the biases of mental models and cognitive heuristics to forecast and promote an appropriate alignment between problem definition and adaptive response sets? The obvious answer is to factor a recognition of these biases into the construction of models. This not only means that urban planners are trained in ways of working within data rich environments, and *in silico* models for anticipating and dealing with the impact of a sudden onset catastrophe (e.g., an earthquake in the centre of Jerusalem) (Grinberger, Lichter, & Felsenstein, 2017). Arguably, this is already a well-established part of an urban planner's tool kit. But, what it also means is that modellers and urban planners must be aware of how bodies (including our embodied cognition) are entangled with culture, utterances, and ecologies.

To briefly explore this point further; this requires urban planners and modellers to problematise and attend to how bodies are produced through our engagements, our entanglements, with technology and smart cities (Deleuze & Guattari, 1987), just as capitalism turns our bodies into working machines (Federici, 2020). When cognition is construed less as the transmission and interpretation of information, but extended biologically to the history of successive adaptations to the organism's niche as a unit of survival (Bateson, 1979; Maturana, 1970), then learning is the recognition that we, as humans, change the environments within which we persist as much as those environments change us in a reciprocal and mutual influence of coupling. We are, in effect, at the wave front of change, always in the process of becoming other as we engage in the reciprocal influence of adaptations with an environment we are changing through our successive adaptations.

The implications of this then are that we should be less concerned with promoting sustainable cities and communities (*pace* SDG 11), but perhaps be seeking to explore how we can avoid those futures which are themselves *unsustainable*. This is to make explicit that we cannot necessarily know what does work; but we certainly can anticipate what does *not* work. We can agree that we can no longer permit the profligate use of fossil fuels due to increasing carbon emissions and changing climate. We can agree that we can no longer support the use of disposable plastics, nor can we support the unfettered destruction of habitats and biomes and the laying to waste of entire ecosystems and the biodiversity which characterises them. To implement this, from the perspective of cognitive cities at least, is to recognise that as we are always in the process of becoming other, our adaptive futures have yet to realised, but the future is already underway. One option for ensuring that future adaptive pathways do not become unsustainable is for cognitive cities to adopt strategic decision support functions. These need to be supplemented by a dialogue decision process which is a "disciplined […] series of structured dialogues between two groups responsible for reaching a decision and implementing the resulting action plan" (Barabba and Pudar, in Sterman, 2000: 43), a process which helps to build consensus around those actions to take. This dialogical process both is informed by and informs critical simulations and models.

This proposal is thus a far cry from the model of smart cities which tend to rely on ICT and Artificial Intelligence (AI) for routine managerial responsibilities. Instead, this proposal argues to include computational resources for the simulation and modelling of scenarios in order to run controlled (and reversible) experiments, modify and update inputs and novel influences and relationships, and to generate multiple outcomes. Through a dialogical process of engagement and an application of the precautionary principle, these scenarios can feed forward into policy and planning as a way of learning from a range of futures, which yield a range of possible typologies for interventions. Moreover, doing so does not require implementation *in vivo* given spatial poverty and the limits to what can be developed from scratch in a city that is already 'live'.

5. The Future Now? Discussion and Conclusions

In this paper, we have proposed, along with other commentators, that the city be reconstrued as an ecosystem, a complex adaptive system, which is in a continuous process of changing the humans who live in it as the humans change it in turn, a natural process termed structural coupling (Maturana & Varela, 1992). Adopting this perspective is to explicitly recognise that the unit of survival is the organism along with its niche (Bateson, 1972). But in making this shift in perspective, we have also discussed the limitations humans face in grappling with complexity, how our mental models simplify and generate linear causal linkages predicated on heuristics and cognitive biases, and how we are ill equipped to make informed decisions about sustainable futures. While some of these cognitive limitations are mitigated somewhat by the use of computer technology to run simulations and to test models, we noted that even these can be constrained by the same biases such models seek to overcome, as in the case of the UK government's response being fitted to previous and familiar models of a flu pandemic despite the data demonstrating a non-flu virus.

As a consequence of the foregoing discussion, we surfaced a point of tension: on one hand we, like others, endorse and advocate the use of *in silico* simulation and experimentation to explore potential threats and opportunities to build in systemic resilience and redundancy to recover swiftly from such threats. Yet, on the other, we have also recognised that good models are built using good data, but if we are cognitively blind to data because it exceeds the scope of our mental models to conceptualise, or because our ways of being with the world are already shaped through structural coupling with a world we have already changed in such cognitively limited ways, then the quandary is this: what constitutes quantitative data that can be realistically and appropriately abstracted to serve as simulation and modelling inputs for future-proofing cities and urban systems? What data are we to collect to inform our models, even given the aforementioned constraints to knowing? How are we going to collect this data for our models and address the ethical issues which may arise?

As it turns out however, this may not be as critical as it at first appears. According to one of the originators of system dynamics modelling, Jay Forrester, we first need to model the system and use the system to inform the data to be collected (Forrester, 1961). He continues that for one to design a "dynamic simulation model […], the factors that must be included arise directly from the questions that are to be answered" (Forrester, 1961: 60). In other words, by using models, we can identify the limitations to what we think we know and respond accordingly. This therefore leads us to ask questions such as what we need to ask in order to model a city as a complex adaptive system? The questions asked will determine the model that is constructed, because trivial or vague questions will lead to trivial or vague responses. Not only then is modelling inherently multidisciplinary, but is also leads to the beginnings of a typology of data, comprising data that is already known; data that can (yet) be captured; data that is needed; and indicative or proxy data.

If our purpose is to model a city as a complex adaptive system then, one that satisfies the ambitions of SDG 11, one that can 'bounce back' following the impacts of a pandemic such as Covid-19, one that can influence its future trajectory, then the questions we may consider asking will include the following: what do we need to conserve now in order to change our *modus vivendi* to facilitate resilience and socio-economic equality? What do we need to do now to avoid unsustainable futures? What do we need to learn from the future to better inform those policies we vote for, those interests being enshrined in governmental decisions, those products we consume and practices we endorse through our roles as 'working machines' (Federici, 2020), entangled with technologies and utterances, culture and ecologies in the on-going processes of becoming other? These are nothing if not a question of ethics (von Foerster & Broecker, 2010), and the decisions we make today determine the options we face downstream.

Naturally, these are not the only ways forward, nor the only strategies available. However, if we do wish to lay the groundwork today for a more sustainable tomorrow, then we do need to adopt a long term view by learning from the future and setting in motion today strategies that will better prepare us for that future. To do so, we do not need smart cities. Rather, we need cognitive cities that adaptively learn, that are agile and that can bring to bear on future threats a range of pre-tested response strategies within a context that has already built in systemic redundancy to facilitate further adaptations.

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