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Planning support systems for smart cities

Christopher Pettit[a,*], Ashley Bakelmun[a,**], Scott N. Lieske[b], Stephen Glackin[c], Karlson 'Charlie' Hargroves[d], Giles Thomson[d], Heather Shearer[e], Hussein Dia[f], Peter Newman[d]

[a] Built Environment, University of New South Wales, Sydney, NSW 2052, Australia
[b] School of Earth and Environmental Sciences, The University of Queensland, St Lucia, QLD 4072, Australia
[c] Centre for Urban Transitions, Swinburne University of Technology, Melbourne, VIC 3122, Australia
[d] Sustainability Policy Institute (CUSP), Curtin University, Bentley, WA 6102, Australia
[e] Cities Research Institute, Griffith University, Gold Coast, QLD 422, Australia
[f] Department of Civil and Construction Engineering, Swinburne University of Technology, Melbourne, VIC 3122, Australia

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ABSTRACT

In an era of smart cities, planning support systems (PSS) offer the potential to harness the power of urban big data and support land-use and transport planning. PSS encapsulate data-driven modelling approaches for envisioning alternative future cities scenarios. They are widely available but have limited adoption in the planning profession (Russo, Lanzilotti, Costabile, & Pettit, 2017). Research has identified issues preventing their mainstream adoption to be, among others, the gap between PSS supply and demand (Geertman, 2016), their difficulty of use, a need for greater understanding of PSS capabilities and a lack of awareness of their applications (Russo et al., 2017; Vonk, Geertman, & Schot, 2005). To address this, a review of five PSS is conducted in the context of four vignettes applied in Australia and applicable internationally. A critical review has been undertaken, demonstrating how these PSS provide an evidence basis to understand, model and manage growing cities. The results suggest that PSS can assist in undertaking key tasks associated with the planning process. In addition to supporting planning and decision making, PSS can potentially enable better co-ordination between city, state and federal planning and infrastructure agencies, thus promoting a multi-scaled approach that improves local and national data sharing, modelling, reporting and scenario planning. The research demonstrates that PSS can assist in navigating the complexities of rapid multi-faceted urban growth to achieve better-informed planning outcomes. The paper concludes by outlining ways PSS address limitations of the past and can begin to address anticipated future challenges.

1. Introduction

The integration of Information Communication and Technology (ICT) into cities over the past two decades has generated interest from urban analysts and theorists alike (Kitchin, 2014a, p. 1). Harrison and Donnelly (2011) list examples of the many potential benefits that can arise, such as: lower resource consumption, improving infrastructure capacity, and coordination of peak demands on energy, water and transportation to improve city resiliency. However, the concept of smarter city planning as enabled through big data, city analytics and modelling is one potential benefit which has not been given sufficient consideration. This paper endeavours to address this gap through reviewing recent case studies in the application of planning support systems in the context of Australia.

When considering smarter cities planning one must first provide a suitable definition of smart cities. There are many and varied definitions. Kitchin (2014a) defines smart cities as those that address technology, economy, and governance - comprised of ubiquitous computing and driven by innovation. Other definitions focus on the various scales addressed by smart cities, such as that from Batty et al. (2012), referring to smart cities as both automated "routine functions serving individual persons, buildings, traffic systems" as well as "ways that enable us to monitor, understand, analyse and plan the city to improve the efficiency, equity and quality of life for its citizens in real time" (p.482). This paper focuses on the latter portion of Batty's definition as we explore how the smart city movement has created renewed opportunity

* Corresponding author.
** Corresponding author.
E-mail addresses: c.pettit@unsw.edu.au (C. Pettit), a.bakelmun@unsw.edu.au (A. Bakelmun), scott.lieske@uq.edu.au (S.N. Lieske), sglackin@swin.edu.au (S. Glackin), charlie.hargroves@curtin.edu.au (K.'. Hargroves), giles.thomson@curtin.edu.au (G. Thomson), h.shearer@griffith.edu.au (H. Shearer), hdia@swin.edu.au (H. Dia), p.newman@curtin.edu.au (P. Newman).

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and interest in data-driven urban modelling to support land-use planning.

Increased automation in the built environment gives rise to big data, which is creating new potential for pattern recognition within cities (Batty, 2015). The rapid growth of big data and its range of uses means it is difficult to define (Kitchin & McArdle, 2016), but recent academic dialogue has set it apart from other data in three areas, the '3 V's': volume, velocity, and variety (Laney, 2001). The components of the multi-V model often change depending on the report (Assunção et al., 2013); other authors have defined '5 V's' (Batty, 2016; Assunção et al., 2013) or '7 V's' (Khan, Uddin, & Gupta, 2014; McNulty, 2014), encompassing the following:

- Volume – depth and breadth of data (Laney, 2001)
- Velocity – speed of transmission (Miller, 2015)
- Variety – type and kind of data (Batty, 2016)
- Variability – degree of inconsistency in data representation (Batty, 2016)
- Veracity – reliability or truthfulness of the data (Assunção et al., 2013; Khan et al., 2014)
- Validity – accuracy of the data for its intended use or application (Khan et al., 2014)
- Volatility – the relationship of the retention period for data sets with their associated storage and security needs (Khan et al., 2014)
- Visualisation – presentation of the data (McNulty, 2014)
- Value – the worth and insights derived from in-depth analysis of the data (Assunção et al., 2013; McNulty, 2014)

This paper focuses on the interpretation of big data for urban planners, primarily the *variety* of data used to assess planning scenarios, its communication to stakeholders through *visualisation* methods, and the added *value* from its addition into traditional urban modelling approaches (Thakuriah, Dirks, & Keita, 2017, pp. 189–208). The *variety* of big data we investigate are those defined by Batty (2016): data produced from real-time sensors, spatial data sensed from satellites, and data based on population and economic forecasts.

The potential to harness big data within the smart city movement creates opportunity for planners to better guide the expected 2.5 billion-person growth in the global urban population between 2014 and 2050 (United Nations, 2014). Planners can now combine population and economic forecasts with temporally and spatially sensed data through digital planning tools. Planning Support Science, a field that continuously develops and improves frameworks for big data sets, has emerged with the increased research and development of digital planning tools (Geertman, Allan, Pettit, & Stillwell, 2017). These tools, called planning support systems (PSS), use the growing presence of big data to help inform more sustainable, productive and resilient city scenarios through data mining, analysis, modelling and visualisation.

Experts believe PSS have the ability to help planners navigate the growing complexities in planning (Vonk & Geertman, 2008). Reactions to urban infill and urban growth in general are often very emotional and create anxiety about the future; Newman (2016) calls this anxiety vs agglomeration and suggests the only way to ease this is by demonstrating in each new development there are multiple benefits that can be fashioned from planned changes. It is even feasible to show how such urban growth can be regenerative to issues like climate change, biodiversity loss, bioregional water and soil issues, as well as providing new employment and services (Newman, Beatley, & Boyer, 2017). These are cultural changes in the planning system. But it will require smart PSS to enable this to happen, allowing city planning to evaluate options more thoroughly and quickly but at the same time in a more engaging way with communities. The hope is that PSS will provide a way to resolve debates of growth versus impact, of agglomeration versus anxiety, in future city planning.

Despite the availability of a range of PSS, there are issues preventing their widespread use and adoption namely, a lack of awareness of available tools and lack of experience with their implementation (Russo et al., 2017; Vonk et al., 2005). To address this concern, this paper will explore the current availability of PSS internationally, focusing on four vignettes demonstrating their application at the regional, metropolitan, precinct, and subdivision scale. These vignettes are undertaken in the Australian context yet the key learnings and recommendations from this research hold international relevance.

2. Literature review of PSS

2.1. The state of smart cities and digital planning

Land-use models were initially developed in the 1960s but became highly criticised within the same decade, largely because of the extent of data collection needed to operate them, their treatment of the city as a static system (Batty, 1971), and their attempt to model too many complexities at once (Lee, 1973). Their top-down, black box modelling approach disempowered urban planners and communities alike in the planning process (Lee, 1973). Critiques of large-scale models led to a sustained period of on-going debate between urban modellers and planning practitioners, perhaps symbolised by the close of MIT's Urban Systems Laboratory in 1974 (Townsend, 2013). GIS was instead used "almost exclusively" to analyse past and current urban conditions (Pettit et al., 2013, p. 351).

Thirty years ago, increased capabilities in micro-computing created renewed potential for digital models to guide long-term planning decision (Harris, 1989). Harris (1989) encouraged the planning industry to move beyond GIS to develop and implement user-friendly, flexible, realistic models that could rearrange data to predict impacts of planning scenarios. A call for a new, integrated framework (Gorry & Morton, 1971) led to the growth of decision support systems (DSS), which "allow decision makers to systematically generate and evaluate a number of alternative solutions" (Klosterman, 1997, p. 50). Spatial decision support systems (SDSS) are one type of DSS, and they usually build on GIS to model and visualise the optimal spatial locations for land uses (Densham & Rushton, 1988; Klosterman, 1997). PSS differ in that they are information technologies used specifically to assist the planning profession (Klosterman, 1997) and like SDSS, often integrate GIS (Geertman & Stillwell, 2009). Geertman and Stillwell (2004) define PSS as a framework that combines:

- Identification of the planning challenge;
- A methodology to guide planning through "analysis, prediction and prescription" (p.293);
- The application of data to inform modelling and design.

PSS initially focused on urban economic and travel-demand modelling (Harris & Batty, 1993) and emerged more comprehensively into the planning field the 1990s (Geertman & Stillwell, 2009). Land-use transport models were developed over the next two decades, and by 2004, at least twenty had been calibrated and implemented (Wegener, 2004). These models offer a mathematical way to isolate and combine the variables impacted by land-use and transport policy, offering more informed predictions than could be obtained from user surveys or empirical observations (Wegener, 2004).

PSS are not the only technology supported approach being used to innovate the urban planning process. Grassroots approaches like civic hacking, which uses open source technology to connect individuals to one another and their surrounding environment (Townsend, 2013), are creating disruption to city operations. Both user-friendly, inexpensive microcontrollers and smartphone app-building are allowing ordinary citizens to become entrepreneurs and city shapers. This is creating an entirely different trajectory of smart city development, especially given the ability of these decentralised developments to spread virally (Townsend, 2013). The disruption caused by civic hacking seems to be a competing strategy to top-down centralised models that seek to