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Big data, spatial optimization, and planning

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Introduction

Spatial optimization represents a set of powerful spatial analysis techniques that can be used to identify optimal solution(s) and even generate a large number of competitive alternatives. The formulation of such problems involves maximizing or minimizing one or more objectives while satisfying a number of constraints. Solution techniques range from exact models solved with such approaches as linear programming and integer programming, or heuristic algorithms, i.e. Tabu Search, Simulated Annealing, and Genetic Algorithms. Spatial optimization techniques have been utilized in numerous planning applications, such as location-allocation modeling/site selection, land use planning, school districting, regionalization, routing, and urban design. These methods can be seamlessly integrated into the planning process and generate many optimal/near-optimal planning scenarios or solutions, in order to more quantitatively and scientifically support the planning and operation of public and private systems. However, as most spatial optimization problems are non-deterministic polynomial-time-hard (NP-hard) in nature, even a small data set will generate a very complex solution space and therefore tend to be very computationally intensive to solve. In addition, the quantification and modeling of different (spatial) objectives and relevant constraints also remain a challenge, which requires further attention from the scientific community.

In the past decade, emerging (spatio-temporal) big data have started to play an increasingly important role in city management and planning, and are changing our perceptions about cities. Without a doubt, we are at the beginning of the big data revolution as society incorporates information technologies into every facet of our existence (Mayer-Schönberger and Cukier, 2013), and this big data revolution will significantly change the way in which spatial optimization techniques are utilized in various planning tasks. Traditional approaches, such as linear programming, need to be recast when solving complex problems involving big data while addressing problems such as land use planning, urban economic modeling, and optimal resource allocation. The goal of such work is to better understand, predict, plan, and manage the future of our cities.

Before proposing this special issue, it is evident that researchers in spatial optimization have faced numerous challenges as well as opportunities brought about by the emergence and development of various kinds of (spatio-temporal) big data apart from the evolution of its own modeling theory and technology. Undoubtedly, these data, coupled with new models and approaches, will help change and improve traditional ways of planning within different contexts, such as land use and urban planning, transportation planning and routing, as well as facility siting. The remainder of this editorial reviews the nexus of these three components, including the research shifts in spatial optimization enabled planning, followed by a paradigm for spatial optimization enabled planning involving big data along with an introduction to the five published articles in this special issue on various topics within this wider umbrella.

Research shifts in spatial optimization enabled planning

Spatial optimization has been broadly used to address various types of planning and management tasks, such as land use and urban planning (Aerts et al., 2005; Cao et al., 2011; Cao and Huang, 2019; Cao et al., 2012, 2020; Ligmann-Zielinska et al., 2008), forest planning and management (Borges et al., 2002; Church et al., 1998; Öhman and Eriksson, 2002; Pukkala and Kurttila, 2005), ecological and environmental resource planning and management (Hu et al., 2015; Klein et al., 2010; Williams et al., 2004; Yu et al., 2020), water resource planning and management (Afshar et al., 2015; Murray et al., 2012; Sidiropoulos and Fotakis, 2016), transportation planning (Church and Cova, 2000; Murray and Wu, 2003; Vazifeh et al., 2018; Xue et al., 2015), and routing (Bowerman et al., 1995; Church and Niblett, 2020; Keenan, 2008; Li et al., 2013; Tu et al., 2015; Xue and Cao, 2016), as well as the allocation of public facilities (Church and Li, 2016; Cova and Church, 2000; Farhan and Murray, 2008; Li et al., 2009; Zhang et al., 2016). In the past two decades, there has been remarkable progress made in this field by scientists and scholars from a variety of disciplines, such as geography, ecology and environment, regional science, operational research, engineering, and urban planning. Most of these studies involving spatial optimization modeling have been directed toward a finer scale, with the support of more effective optimization models, as well as more efficient optimization problem solving capabilities from well-adapted heuristic approaches, high performance computing (HPC) and methods to trim superfluous features from spatial optimization models, making them easier to solve without compromising on the task of finding optimality (Church, 2018). Alongside the rapid development of information and communications technology as well as the empowered availability of (spatio-temporal) big data and analytics capabilities (Li et al., 2020), there have been a few notable shifts in the field of spatial optimization enabled planning in the past few years, which shed light on not only the opportunities and insights in this field, but also the challenges that are worth more attention from scientists and scholars in the future.

The first notable shift is the transition from small data-based spatial optimization to (spatio-temporal) big data-based spatial optimization studies. The emerging big data in the past decade, such as data sources from smart phones, smart card transactions, and the Internet of Things, have brought forward massive opportunities in a broad range of disciplines by its finer granularity and the new angles for addressing various research issues, including spatial optimization and planning related research questions. Meanwhile, the velocity, volume, and variety of big data also pose huge challenges. One example is the research on addressing the minimum fleet problem serving on-demand urban mobility by Vazifeh et al. (2018). They address how best to size and operate a fleet of vehicles, given a certain demand for personal mobility. This has been modeled using spatio-temporal data associated with more than 150 million trips and 13,586 taxicabs in New York City in 2011. The proposed method identified an optimal solution for an entire year of operation. A real-time implementation produced a near-optimal solution that involved a 30% reduction in the needed fleet size compared to the current taxi operation. The implementation of big data in spatial optimization not only enables a more detailed spatial optimization process at a finer scale, but can also empower a shift from static spatial optimization to dynamic/real-time spatial optimization applications. Undoubtedly, spatial optimization supported by big data is an appealing direction that will play a critical role in many optimization problems in the era of smart cities. Without a doubt these new developments demand more attention from academia and industry.

The second notable shift is the transition from spatial optimization to spatio-temporal optimization studies. One of the common challenging issues is the optimization of both spatial and temporal dimensions. For example, the spatial optimization for land use planning is able to determine the optimal or near-optimal land use planning scenarios in terms of "where" and "how much" different land use types or activities should be allocated. Another critical issue involved is "when" or "how" to optimally transit to a given land use planning target scenario across time, which might be extremely complicated and computationally intensive. Cao et al. (2019) have developed a multi-objective, spatio-temporal land use optimization model to determine the possible spatial land use planning solutions over time through a novel hierarchical and back-tracing strategy. The proposed model was implemented effectively and successfully in a case study of the Wuhan urban agglomeration region. There were, however, limitations, including the resulting computational efficiency and the limited exploration of the solution space. Of course, spatio-temporal optimization would be empowered by the integration of (spatio-temporal) big data; however, it is also a challenge to address the resulting complexity that big data dimensions present. It is still the dawn of this new era and considerable advances are expected along this front.

The third shift is the transition from the traditional applied disciplines, e.g. business, planning, ecology, and engineering, to the disciplines of social and behavioral sciences, such as health and ageing, criminology, and epidemiology. At the same time, given the current vision of spatially integrated social sciences (Goodchild et al., 2000), spatial optimization approaches are more than just good additions to the existing pool of methods for spatially integrated social sciences, helping to form an enhanced version of spatially integrated social and behavioral sciences. One example is the research of location-allocation modeling of healthcare facilities by Zhang et al. (2016). In addition to the gravity-based accessibility model implemented in the research, a multi-objective optimization model was also constructed and utilized to help quantitatively identify the optimal configurations of public healthcare facilities in Hong Kong. It is evident that spatial optimization approaches could supplement fundamental GIS functions: spatial statistics and visualization. But the lack of user-friendly and effective spatial optimization tools is one of the main barriers to social scientists working in this field, especially when (spatio-temporal) big data are involved.

A paradigm for spatial optimization enabled planning in the era of big data

As discussed above, most of these research shifts are directly or indirectly affected by the booming availability of spatio-temporal big data (e.g. smart card data and smart phone data), and new big data analytics capabilities. The opportunities and challenges, brought by the big data era, represent an evolving new paradigm in spatial optimization enabled planning (see Figure 1).

In this special issue, we received dozens of submissions, where five papers were finally accepted for publication, all of which reflect various facets of this paradigm.

Zou et al. (p. 948) combine machine learning, big data, and spatial optimization to produce time-sensitive routes to avoid poor air quality when travelling across an urban region. Using a deep learning approach, namely the long, short-term memory and city-level air quality data, the proposed machine learning model is capable of making temporal predictions of air quality across an urban area. Using air quality predictions, a spatial

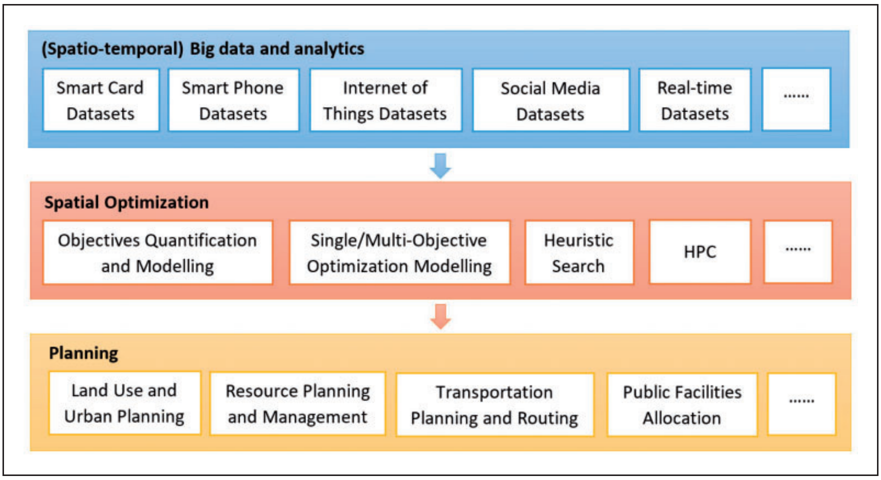

Figure 1. A paradigm for spatial optimization enabled planning in the era of big data. HPC: high performance computing.

optimization model is developed for planning a suitable path that optimizes both distance and overall air quality. This work has significant value in helping cyclists, hikers, and other people engaged in outdoor activities to plan ideal travel routes to stay active and healthy.

Yin et al.'s (p. 964) work aims at resolving the computational complexity in evacuation route planning in the midst of urban disasters. Their approach is to derive, in advance, a spatial distribution of the population of a region from mobile phone location data. Based on this information, a knowledge base is developed to store the optimal evacuation routes given the known population distribution. When a disaster occurs, the information within the knowledge base is leveraged to search for near-optimal evacuation routes using agent-based modeling. This work sheds light on combining data-driven and knowledge-based approaches to develop efficient solutions for applications with a real-time requirement, such as emergency evacuation.

The paper by Mu and Tong (p. 981) develops a computationally efficient solution to tackle large p-median optimization problems. The p-median problem aims to allocate p facilities in a study area to minimize the overall cost (sum of travel distances) from any demand node to the nearest facility. Given the NP-hard nature of the problem, the optimal solution is extremely difficult to obtain when applied to very large problems (as measured by the number of demand nodes and facility sites). To address this problem when applied to big data, the authors develop a heuristic algorithm to partition the problem into smaller, sub p-median problems and solve them in parallel, leveraging HPC. The solutions are then combined strategically into the final solution using a spatial voting algorithm. This research represents an important step toward solving big data spatial optimization problems. The ability to solve large p-median problems has important real-world use and can be of significant value.

Koenig et al. (p. 997) present an interesting and integrative framework for urban design and planning. The paper starts with defining a holistic data representation of urban fabric, including various urban factors, such as a street network, land parcels, etc. that influence design decisions. Based on this definition, the authors demonstrate a computational approach for integrating this unified data structure in a software called Grasshopper, which supports the solution of Rhino3D, a commonly used optimization system for addressing urban design problems. By relying on such a framework, contradicting design goals can be reconciled, and a semi-automated design process can be achieved. This research was shown to be of great value in major master-design planning projects for smart cities.

The final paper in this special issue by Church and Baez (p. 1014) involves an aspect of spatial optimization that many planners and researchers tend to ignore when using a model in spatial design. Making decisions based on what was found as the optimal or best heuristic solution fails to consider errors in problem data that might preclude the true optimal solution from being found, overlooks the fact that decision makers may have not fully divulged all of their objectives or preferences, and discounts the key issue that most models are simplified forms to make them solvable to optimality. Church and Baez discuss how models could better assist in the search for competitive but different configurations of spatial optimization problems. They present a new "tree-based" search method that can be used to find all multiple optima or all near-optimal configurations to many facility location problems. They apply their approach to two widely used location models and demonstrate that there can be a rich and varied set of near-optimal configurations with which to better support decision makers and stakeholders. They also compare their new process to the current standard approach and show significant improvement in computational efficiency, paving the way for greater opportunities to generate different but competitive spatial alternatives.

Concluding remarks

While these five articles have solved different spatial optimization problems involving various facets of the paradigm mentioned above, we admit that the articles in this special issue have explored a very small subset of the types of problems that exist within the scope of applied spatial optimization and big data. We hope that this issue will stimulate readers to develop more related research ideas and actively contribute to the development of spatial optimization enabled "smart" planning in the era of big data.

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