A multi-objective spatial optimization framework for sustainable urban development

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ABSTRACT

Future urban development must address climate-related risks, increasing populations and multiple sustainability objectives. This includes reducing development on green space; reducing flood risk; reducing urban sprawl; improving access to public transport; prioritising brownfield development and; reducing urban heat island. Decision makers are therefore confronted with the challenge of achieving multi-objective spatial optimization to determine synergies and trade-offs between sustainability objectives and various risks. Multi-objective optimization (MOO) methods are typically adopted within spatial optimization applications due to their ability to provide best possible trade off solutions to multiple objectives. However, the application of such methods within urban planning is limited due to the specialist knowledge required to facilitate the development of MOO frameworks. This paper explores the abilities of evolutionary computing techniques as a method to support multi-objective spatial optimization. The MOSO framework is applied to a number of UK-based case studies, two of which are presented within this paper (Greater Manchester and West Yorkshire). The study compares a set of spatial development plans and pareto-optimal fronts for each region and highlights the capability of multi-objective spatial optimization as a decision support tool within urban planning.

Keywords: sustainable development goals, multi-objective optimisation, cloud computing, spatial planning

INTRODUCTION

The frequency of weather catastrophes has increased at a global level throughout the last century. These events are expected to continue increasing due to the unprecedented impact of future climate change (Monirul & Mirza, 2003). It is estimated that by 2030 over 5 billion people will reside within cities (Ash et al., 2008), however, many urban regions are considered to be situated within high risk locations (Carter, 2011). Additional influences, such as urban heat island and increased impermeable surfaces, may further exacerbate the exposure and vulnerability factors associated with urban populations (Hunt & Watkiss, 2011). Furthermore, an increase in weather catastrophes, temperature and other climatic parameters can ultimately effect infrastructure networks within urbanised regions, therefore hindering development and causing a negative socio-economic feedback (Vorosmarty et al., 2000; Gill et al., 2007; CCSP, 2008). Contemporary research has therefore shifted its focus upon assessing the resilient capabilities of urban environments by reviewing current sustainable development practices (Carmin et al., 2009; Prasad, et al., 2009; Novotny et al., 2010). Unmitigated climate change is subsequently incompatible with sustainable development due to its impact upon society and the natural environment, consequently jeopardising the economic integrity of a particular city, region or country (Swart & Raes, 2007). In response to this, spatial planners are encouraged to adopt robust heuristic methods (van Buuren et al., 2013), such as spatial optimization (SO) (Chen et al., 2015) and multi-objective optimization (MOO) (Cao et al., 2011), to determine the best possible solutions required to reduce economic, social and environmental deterioration as a result of expected climatic change.

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Multi-objective spatial optimization (MOSO) allows the user to evaluate and compare a wide selection of local optimal solutions whilst simultaneously addressing multiple optimization objectives, therefore allowing complex optimization problems to be assessed (Zhang et al., 2010). Such methods are vital to address the full spatial and temporal dynamics associated with the spatial development of urban environments (Malakzadeh et al., 2010). However, the objectives evaluated within MOO problems are likely to encompass a variety of trade-offs and synergies. In such cases, spatial planners are often confronted with conflicting options for solutions over multiple sets of objectives or priorities when considering large and/or complex spatial domains. Evolutionary computing methods, such as genetic algorithms, have been used alongside traditional spatial optimization strategies to enable the application of MOSO within complex case-studies (Aerts et al., 2005; Jiang-Ping & Qun, 2009; Caparros-Midwood et al., 2015). Although the integrity of these methods is widely acknowledged, the coupling of such techniques is not common practice within urban planning due to the specialist understanding required to build a MOSO framework and only a handful of existing real-world applications exist (Caparros-Midwood et al., 2016).

This paper explores the capabilities of coupling evolutionary computing methods with spatial optimization techniques to assess multiple conflicting objectives within large complex spatial domains. The framework was applied to individual cities within the Northern Powerhouse (NPH) region of Northern-England (Figure 1a and 1b) and this paper presents spatial development plans for two city-regions within NPH (Greater Manchester and West-Yorkshire). These plans aim to improve access to public transport; reduce urban heat island, flood risk and urban sprawl; limit green space development and; prioritise brownfield site development. The information will be used to devise a portfolio of optimized spatial development plans that feature trade-off solutions to conflicting sustainability objectives and prime locations for low-risk and sustainable housing.

![Figure 1](image_url) (a) An overview of the UK and the various regions assessed by the MOSO framework presented within this paper and (b) the urban and non-urban areas of the NPH region.

**METHODOLOGY**

The objectives of the framework were selected to reflect real-world sustainable development priorities for the UK (Figure 2). To visually represent these objectives, a variety of nationally available datasets were exploited within ArcMap 10.3. For example, Ordnance Survey MasterMap data was used to collate data for greenspace sites and brownfield sites, whereas flood data was collected from the environment agency’s (EA) flood-zone maps and rasterised at 100 metre spatial resolution. A technique to characterise Public Transport Accessibility Levels (PTAL) was employed to quantify the connectivity of each potential development site to public transport (Shah & Adhvaryu, 2016).

The study employs a multi-objective spatial optimization framework (Caparros-Midwood et al., 2016) which utilises a non-dominated sorting genetic algorithm (NSGA-II, Figure 3). The Distributed Evolutionary
Algorithms for Python (DEAP) module was employed to implement the key evolutionary operators necessary for the genetic algorithm optimization. The NSGA-II uses selection, crossover and mutation evolutionary operators to converge previous sets of spatial development plans and ensure more optimal solutions are achieved within proceeding generations (Figure 3). A value of 0.7 was applied to the crossover operator and 0.2 to the mutation operator to represent the probability of mating and mutating an individual (Keirstead & Shah, 2013). The framework was executed for 100 generations, each generation producing a set of pareto-optimal results for pairs of sustainability objectives. This method was applied to all NPH regions noted within Figure 1b to determine the various trade-offs and synergies between sustainability objectives that may occur at city-region level.

**Figure 2** The objective functions represented within the multi-objective spatial optimization framework (reducing sprawl = \( f_{\text{sprawl}} \); reducing flood risk = \( f_{\text{flood}} \); reducing heat risk = \( f_{\text{heat}} \); reducing greenspace development = \( f_{\text{greenspace}} \); and prioritising brownfield development = \( f_{\text{brownfield}} \)) and an illustration of how this has been visualised within the raster data layers.
RESULTS AND DISCUSSION

Figures 4a and 5a present examples of optimized spatial development plans for Greater Manchester and West Yorkshire, highlighting potential sites for low-risk housing development. Figures 4b and 5b show normalised pareto fronts produced by the multi-objective spatial optimization framework for these regions. In this example, the pareto fronts present two objectives, reducing urban sprawl and reducing risk from heatwaves. It is apparent that the spatial domains attain a number of similarities within the development plans i.e. major development seems to cluster around the CBDs with smaller clusters existing within the rural corridors outside of the urban periphery. This is most likely due to the framework aiming to achieve a reduction in urban sprawl whilst also aiming to increase access to public transport, whereby both objectives encourage development within, or close to, urbanised regions. The pareto-fronts denote a noticeable contrast between the two spatial domains (figures 4b and 5b). Figure 4b highlights that the area of Greater Manchester displays a higher maximum range along the pareto-front when compared to Western Yorkshire. Greater Manchester has a pareto front that extends to a maximum value of 0.179 for fheat and 0.83 for fsprawl compared to West Yorkshire which ranges from 0.168 to 0.59 respectively. This may imply that the magnitude of conflict between heat and sprawl objective functions was higher when formulating optimal spatial solutions for Manchester. This reflects the complexity of spatial planning that is common within large, complex spatial domains such as the City of Manchester.
Figure 4 (a) Spatial development plan highlighting proposed development sites and (b) pareto front results for Greater Manchester showing heat and sprawl objective function values.
Figure 5 (a) Spatial development plan highlighting proposed development sites and (b) pareto front results for West-Yorkshire showing heat and sprawl objective function values.
The number of solutions situated along the pareto-front also differs amongst the spatial domains; Manchester offers 19 solutions compared to Leeds which offers 10. These values highlight the magnitude of conflict experienced by the framework when considering \textit{fsprawl} and \textit{fheat} for Western Yorkshire and Greater Manchester. A higher number of solutions typically implies a more challenging spatial domain where synergies between objective functions is difficult and more trade-offs may occur. This evidence again reflects the difficulties associated with the planning of spatial development within more complex urbanized regions such as Manchester due to the higher vulnerability factors associated with densely populated cities. Regardless of these conflicts, the MOSO framework manages to provide a set of spatial development plans that provide the best possible trade-off solutions for multiple objective functions.

CONCLUSION

In light of the findings presented within this paper, it is evident that the framework provides a method to support evidence based decision making in urban planning. The framework was applied to a number of case-studies to assess real-world scenarios for spatial domains that range in size and complexity. The use of pareto-optimal results also determines the possible trade-offs and synergies that occur between objectives and facilitates comparison between spatial domains. Despite the presence of conflicts between the various sustainability objectives, the framework provides a conceivable portfolio of spatial development plans whilst considering all objectives simultaneously. In addition to existing work on the Greater London Authority (Caparros-Midwood, 2016), the framework may also be used to advise spatial planning decisions within the NPH region. The flexibility of the framework also allows alternative objective functions (such as water scarcity, deprivation index, land-value etc.) to be included within the framework during later stages of model development. A temporal aspect should also be included within future stages of model development to reflect uncertainties associated with future climate, air quality and transport projections. By doing so, the user may be able to simultaneously assess a variety of sustainability objectives at a national, regional and local level to provide the UK with the next generation of spatially optimized development plans that account for future climate induced risks as well as sustainability and ecological service objectives.

ACKNOWLEDGEMENTS

This research is funded by the Natural Environment Research Council, grant ref: 1808521 and is part of the Data, Risk and Environmental Analytical Methods (DREAM) centre for doctoral training.

REFERENCES


