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Systematic Review

Computational Optimisation of Urban Design Models: A Systematic Literature Review

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Abstract: The densification of urban spaces globally has contributed to a need for design tools supporting the planning of more sustainable, efficient, and liveable cities. Urban Design Optimisation (UDO) responds to this challenge by providing a means to explore many design solutions for a district, evaluate multiple objectives, and make informed selections from many Pareto-efficient solutions. UDO distinguishes itself from other forms of design optimisation by addressing the challenges of incorporating a wide range of planning goals, managing the complex interactions among various urban datasets, and considering the social–technical aspects of urban planning involving multiple stakeholders. Previous reviews focusing on specific topics within UDO do not sufficiently address these challenges. This PRISMA systematic literature review provides an overview of research on topics related to UDO from 2012 to 2022, with articles analysed across seven descriptive categories. This paper presents a discussion on the state-of-the-art and identified gaps present in each of the seven categories. Finally, this paper argues that additional research to improve the socio-technical understanding and usability of UDO would require: (i) methods of optimisation across multiple models, (ii) interfaces that address a multiplicity of stakeholders, (iii) exploration of frameworks for scenario building and backcasting, and (iv) advancing AI applications for UDO, including generalizable surrogates and user preference learning.

Keywords: urban design optimisation; optimisation frameworks; generative modelling; solution space exploration; surrogate models

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1. Introduction

The planet is rapidly urbanizing, with the current urban population standing at 4.4 billion, which constitutes approximately 70% of the global population, and is projected to double by 2050 [1]. In the face of escalating urban densification, addressing the repercussions of inadequate urban planning and design emerges as a critical imperative. The risks of poor planning are exemplified by the traffic congestion in Mumbai [2], the need for disaster preparedness in Haiti [3], the misaligned land use in Detroit [4], and the chaotic growth patterns in Manila [5]. While the root causes of these lapses can be specific to each case, these cases all highlight the importance of evidence-based planning incorporating capabilities for long-term foresight on urban climate, use scenarios, and risks.

Modelling and simulation in urban analytics contribute to evidence-based planning by offering predictive capabilities for trend forecasting and developing robust theoretical frameworks to understand urban systems [6]. Among urban analytic techniques, the optimisation of urban design models comprises methods of simulating dozens or even thousands of design options in search of solutions that best meet planners' desired criteria. Practitioners and researchers use these methods to analyse present conditions and explore solutions to anticipated urban challenges.

Commercial tools for urban design released in recent years attest to the growing relevance of modelling and simulation in urban planning. Webtools developed by Delve from Sidewalk Labs and Spacemaker have been marketed as a means to maximize the profitability and sustainability of urban development [7]. The growth of these commercial urban design optimisation tools has overlapped, not coincidentally, with the increased accessibility of urban big data and a surge in interest in urban analytics [6].

Urban design optimisation (UDO) is a process which implements a cyclical approach involving the generation, evaluation, and optimisation of design solutions. Solutions are generated using a parametric model defined by design rules and constraints. An evaluation model analyses these solutions using objective functions to produce quantitative scores. These scores help to direct an optimisation solver in search of improved solutions by adjusting the parameters used by the parametric model. The resulting solution space can be presented to users with a variety of methods, ranging from simple tabulation to interactive interfaces. Finally, these steps are encapsulated within an optimisation framework, serving as an organization schema for UDO. A typical UDO process is visualized in Figure 1 and illustrates the case of a problem definition solved using multiple-objective optimisation by iterating many models with unique evaluation criteria concurrently. UDO distinguishes itself from other forms of design optimisations by addressing the challenges of incorporating a wide range of planning goals, managing the complex interactions among various urban datasets, and considering the social–technical aspects of urban planning involving multiple stakeholders.

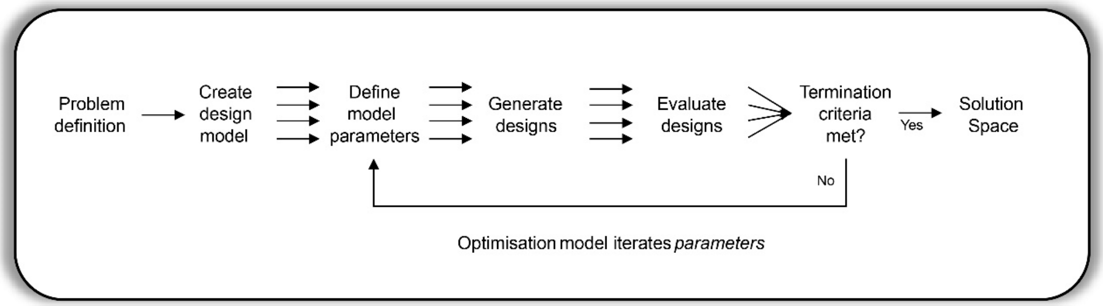


Figure 1. Diagrammatic framework for UDO. Multiple arrows indicate that a single problem definition can be solved using various models during the iterative process.

With increasing numbers of optimisation objectives and types of urban models, UDO faces the challenge of becoming computationally intractable or difficult to interpret for most planners or stakeholders [8,9]. The complexity of UDO shares characteristics with what design studies refer to as 'wicked' problems, problems in which reformulations are always possible, no consistent stopping condition is defined, and differing formulations produce differing results [10,11]. In the context of UDO, models, objective functions, and optimisation methods may be combined to create optimisation frameworks that are customized for specific project requirements. Turcu [12] describes the complexity of goal setting for urban sustainability as having 'no blueprint, but multiple pathways' and emphasizes that a fixed set of sustainability indicators will not capture the circumstances, priorities, and goals of a local community. Batty [13] has challenged the prevalence of single-model urban studies, indicating the need for further work on the use of multiple models in ensemble forecasting or counter-modelling. Mikovits [14] similarly argued for expanding beyond single-scenario urban modelling to better capture the complexity and potential of urban systems.

Caniglia et al. argue underemphasis on socio-technical and transdisciplinary aspects in sustainability research [15]. This argument reflects the trends observed in this literature review, which includes increasing emphasis in UDO research on data analytics, machine learning, and interactive interface design. From this argument, we propose future directions in research on complex UDO and present schematic methods for applying solution space exploration across multiple-model, multi-objective optimisation frameworks.

The paper is organized as follows: Methodology introduces the methods used to select papers for review and the logic of the categorisation applied; Results and Discussion analyse the reviewed literature based on seven categories; Future Directions and Conclusions identify research trajectories for UDO based on observations from the reviewed literature and the study conclusions.

2. Methodology

This review integrates literature across urban planning, urban analytics, urban design, and computer science to identify significant challenges and research gaps in UDO research. The methodology employed for selecting articles to review follows the "Preferred Reporting Items for Systematic Reviews and Meta-Analyses" (PRISMA) framework, which includes the phases of identification, screening, and inclusion conducted by the first and second authors in this paper [16]. The framework is illustrated in Figure 2.

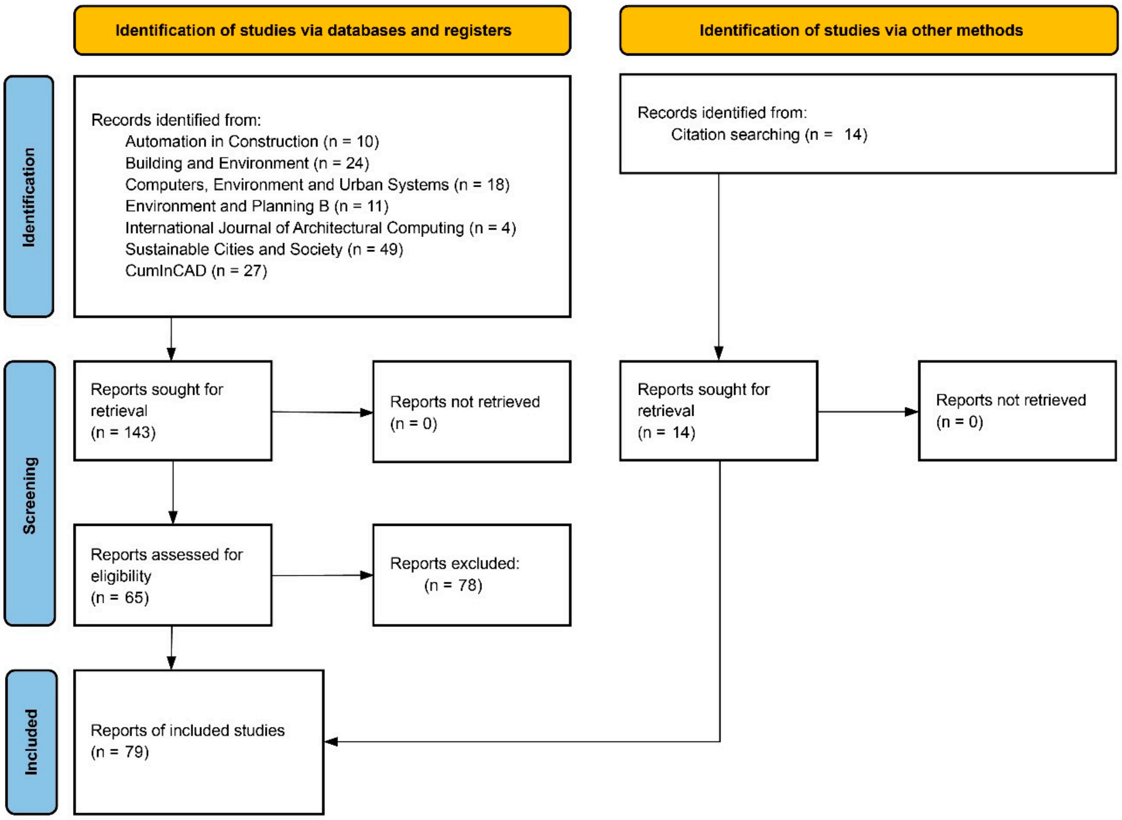


Figure 2. Procedure for literature search.

Our method for identifying articles to include involves searching with keywords, filtering by relevant journals, applying date filters, and screening for topic relevance. The strategy used for selecting search terms considers the absence of a formal definition for topics encompassed within UDO. During the identification phase, a wide range of results is captured using the broad search terms "Urban" and "Optimisation". This search permitted the identification of a wide range of literature while avoiding the potential bias of method-specific search terms. This broad and comprehensive initial search is then screened and sorted to highlight only those articles relevant to UDO.

To improve the relevance of the articles to be screened, we searched only the databases of journals and conferences related to the computational design of urban-scale spaces or architecture. We excluded peripherally relevant topics such as urban policy, social issues, and ecosystem science to concentrate on the optimisation of the physical parameters of planning and urban design. The selected journals include "Automation in Construction", "Building and Environment", "Computers Environments and Urban Systems", "Environment and Planning B", "International Journal of Architectural Computing", and "Sustainable Cities and Society". Due to the high relevance to computer-aided architectural design, we also included articles from various architectural research associations using the Cumulative Index about articles in Computer-Aided Architectural Design (CumInCAD) database. Finally, we only included articles published between 2012 and 2022 to ensure the relevance of the content. From this identification phase, 143 articles were retrieved and screened.

The screening process included examining the abstract and the main body of work in each article. Articles where authors applied optimisation to spatial urban models and had clear applications to urban planning or design were included. On the other hand, articles optimising non-spatial models and smaller-scale building subsystem models were excluded. After screening, 78 articles were excluded. Additionally, 14 articles were identified from citation searching by known authors in this field. In total, 79 articles are studied and compared in this review paper. From the 79 articles, we found a total of 216 authors contributing to this field, of which 22 authors contributed more than once.

This review is structured by grouping articles using seven categories that define distinct trajectories of research for UDO. Beginning with the broadest topic, the categories are: (i) goals and objectives; (ii) model types; (iii) model generation; (iv) optimisation algorithms; (v) surrogate models; (vi) solution space exploration; and (vii) optimisation frameworks. Some of these categories have been studied in previous reviews, such as goals and objectives [17], optimisation algorithms [18], and surrogate models [19]. However, no prior review has cross-analysed all the above UDO research topic categories, nor has any prior review traced the emerging importance of socio-technical research in UDO.

Within each category, subcategories are defined to assist with discussion. For example, in Section 3.2 under model types, we further distinguish between network models, raster models, and 3-dimensional models, as each of these model types warrants its own discussion. Trajectories within each category and subcategory are explored via tabulation and time-based bar charts to quantify the emergence and prevalence of topics within the field. An in-depth discussion of specific articles within each category/subcategory provides an overview of the state of the art, challenges faced, and future research directions.

3. Results and Discussion

This section reviews each of the seven analytic categories of UDO individually. Articles that are relevant to multiple categories of UDO are included in each relevant subsection.

3.1. Goals and Objectives of Urban Design Optimisation

This section extracts the optimisation objectives from the reviewed papers and further categorises them for comparative analysis according to five types of goals. A total of 57 (72%) articles have been identified to have applied and discussed results from optimisation. The five goals of UDO defined in this section are (i) density; (ii) outdoor comfort; (iii) natural resource; (iv) cost; and (v) liveability (Table 1). This list of goals is not exhaustive and is presented as a comparative framework for the purposes of this literature review. Articles categorised under a single goal are not necessarily a single-objective optimisation study but may in fact optimise multiple similar objectives grouped here under a single goal. This section first discusses general trends observed across all five goals, followed by further analysis of each goal in the following five subsections.

The density goal primarily addresses the optimisation of metrics based on population and distance. The cost goal addresses the optimisation of financial-based inputs and outputs during the construction and operation phases of the project. The natural resource goal brings together studies of optimal use of limited resources, such as land, water, and power. The outdoor comfort goal includes articles that optimise experiences in public spaces by considering environmental factors such as wind speeds, humidity, and sunlight. The liveability goal includes articles that optimise measures related to quality of life.

Table 1. Categorising articles by goals addressed, including natural resource (NR), outdoor comfort (OC), cost (CO), density (DE), and liveability (LI).

Author, Date	DE	OC	NR	CO	LI	Author, Date	DE	OC	NR	CO	LI
Delmelle et al., 2012 [20]	x					Gerber et al., 2012 [21]				x	
Kaushik & Janssen, 2012 [22]			x			Chee & Janssen, 2013 [23]	x				
Chen et al., 2013 [24]			x	x		Choo & Janssen, 2013 [25]			x		
Choo & Janssen, 2014 [26]			x			Haque & Asami, 2014 [27]	x			x	
Caparros-Midwood et al., 2015 [28]	x				x	Conti et al., 2015 [29]			x		x
Doe & Aitchison, 2015 [30]			x			Makki, 2015 [31]	x	x			x
Koenig, 2015 [32]					x	Si & Wang, 2015 [33]			x		
Taleb & Musleh, 2015 [34]		x	x			Vermeulen et al., 2015 [35]			x		
Wang & Guldmann., 2015 [36]				x		Zhang et al., 2015 [37]	x		x		
Koenig & Varoudis, 2016 [38]	x					Mohammadi et al., 2016 [39]	x				x
Tong, 2016 [40]	x					Zhang et al., 2016 [41]	x			x	
Chen & Janssen, 2017 [42]			x		x	Juan et al., 2017 [43]		x			
Ma et al., 2017 [44]	x					Zhao et al., 2017 [45]					x
Bizjak et al., 2018 [46]			x			Du et al., 2018 [47]		x			
Makki et al., 2018 [48]	x	x			x	Yao et al., 2018 [49]	x				
Du et al., 2019 [50]		x				He et al., 2019 [51]				x	
Javanroodi et al., 2019 [52]			x			Yao et al., 2019 [53]				x	
Zhong et al., 2019 [54]	x					Düring et al., 2020 [55]	x	x			
Kaseb et al., 2020 [56]		x				Koenig et al., 2020 [57]	x				
Tang et al., 2020 [58]	x			x		Wang et al., 2020 [59]			x		
Wang et al., 2020 [60]	x			x		Zhang et al., 2020 [61]		x			
Genre-Grandpierre et al., 2021 [62]	x					Shirzadi & Tominaga, 2021 [63]		x			
Wang et al., 2021 [64]		x			x	Wu et al., 2021 [65]		x			
Wu et al., 2021 [66]		x		x		Zhao, 2021 [67]			x		
Zhuang & Lu, 2021 [68]		x				Duering, 2022 [69]		x	x		
Kaseb & Rahbah., 2022 [70]		x				Li et al., 2022 [71]		x			
Lima et al., 2022 [72]	x					Ma & Ameijde, 2022 [73]				x	x
Martínez-Bernabéu &Casado-Díaz, 2022 [74]	x					Showkatbakhsh & Makki, 2022 [75]	x				x
Xie et al., 2022 [76]		x									

To extract overall insights on the goals and objectives addressed by contemporary UDO research, the number of articles addressing single and multiple goals are tabulated below (Table 2). A total of 38 (67%) of the reviewed articles applying optimisation address only a single goal type. Optimising for cost with density [27,41,58,60], and density with liveability [28,31,39,48,75] are the most common pairs of goals addressed in the same article. The only combination of three goals addressed in a single article identified included the goals of outdoor comfort, density, and liveability [31,48]. The goal of liveability is most often combined with others, as 9 out of 11 articles addressing this goal also address at least one other goal. This reflects that liveability objectives are commonly used to trade-off with other goals during multi-objective optimisation.

From the results in Table 2, it is observed that there is a lack of research addressing multiple goals. This may be due to the necessity to remain focused on the specific topic under investigation. Single-goal UDO research does not reflect the multidisciplinary nature of planning and urban design practice, where multiple goals must be considered to better inform decision-making. On the other hand, implementing multiple goals increases complexity, particularly when using multiple model types (Section 3.2) and exploring the solution space of high-dimensional results (Section 3.6).

Table 2. Tabulation of articles addressing single and multiple goals. Combinations of multiple goals addressed in one article are grouped with a dash symbol.

Total Articles Including		Articles Addressing Single Goal		Articles Addressing Multiple Goals	
Goal	**Count**	**Goal**	**Count**	**Goal Combination**	**Count**
DE	22 (28%)	DE	11 (14%)	CO-DE	4 (5%)
OC	18 (23%)	OC	11 (14%)	DE-LI	3 (4%)
NR	16 (20%)	NR	10 (13%)	NR-LI, OC-DE-LI, NR-OC	2 (3%)
CO	11 (14%)	CO	4 (5%)	NR-DE, OC-DE, OC-LI, OC-CO, CO-LI, NR-CO	1 (1%)
LI	11 (14%)	LI	2 (3%)		

3.1.1. Density

The density goal covers 22 (28%) of the reviewed articles that optimise for density-related urban objectives. These objectives include accessibility, compatibility, compactness, distribution, and transport costs. Accessibility explores how density can influence the ease of reaching different amenities or destinations within an urban area [20,41,54,55]. Compatibility studies examine how the coexistence of different land uses within a compact area can optimise urban functionality and liveability [27,39,44,74]. Compactness addresses the spatial arrangement and physical form of urban elements to minimize land use inefficiency [37,39,44,58,72]. Distribution examines the spatial distribution of patterns of density and optimises its impact on urban functionality, social dynamics, and infrastructure development [31,40,48,57,60,75]. Transport cost is typically studied as a distance-based metric to address transportation efficiency and walkability within urban areas [23,28,38,49,62].

3.1.2. Outdoor Comfort

The outdoor comfort goal is addressed in 18 (23%) of the reviewed articles, covering both wind and thermal comfort. These articles primarily address wind velocity, sunlight exposure, ambient temperature, or a combination of these factors. Among the reviewed articles, wind comfort is more commonly addressed than thermal comfort [43,47,50,55,56,63–66,69,70]. Solar irradiance analysis is also employed for outdoor thermal metrics such as ground sunlight exposure and shade coverage [31,34,48,61,69,71,76].

In addition to focusing on the impact of climatic factors on thermal comfort, more complex outdoor thermal comfort indices have been used as optimisation objectives. Wang [64] incorporated the Universal Thermal Climate Index (UTCI) in their studies to optimise the layout of high-rise buildings. UTCI is a comprehensive index that considers temperature, relative humidity, solar radiation, and wind speed [77]. Du et al. [50] employed the Psychological Equivalent Temperature Index (PET) in their analysis to optimise building massing for lift-up design, which directly translates thermal stress into thermal comfort [78]. In another approach, Li et al. [71] focused on calculating biogenic net ecosystem exchange (NEE) by subtracting the total respiration from soil and vegetation from the gross primary production from trees and lawns. A negative NEE value indicates a net carbon sink. Zhuang and Lu [68] implemented a simplified approach to optimising urban temperature by analysing land use and roof cover of buildings in Hong Kong and additional biophysical parameters, including evapotranspiration, shade, albedo, and crop coefficient.

3.1.3. Natural Resource

The natural resource goal is addressed in 16 (20%) of the reviewed articles. These articles primarily focused on optimising the use of energy, water, or other resources, with the majority seeking to minimize energy consumption in buildings. The related objective of minimizing the cost of heating and cooling is also included under this goal. The most addressed objective under the goal of natural resource is the optimisation of energy efficiency in buildings by minimizing heating and cooling requirements [22,24–26,29,30,34,42,46,52]. Maximizing daylight hours to reduce energy consumption is another significant focus under this goal [33,69]. Additionally, several articles maximized solar irradiation for photovoltaic (PV) panels through positioning and configuration [35,59,67]. Finally, optimising land as a resource for sustainable urban expansion has been studied via land use allocation simulation [37].

3.1.4. Cost

Cost goals are addressed by 11 (14%) of the reviewed articles. Optimisation of profit from the sale of land or buildings is the most common goal in this category [21,27,58,66]. Similarly, Chen et al. [24] applied optimisation to minimize costs based on materials used for construction. Six articles focus on minimizing the costs, including relocation costs [51], floor plate construction costs [73], damages from seismic activities [36], and the provision of critical infrastructure [41,53,60]

3.1.5. Liveability

The liveability goal regroups 11 (14%) articles that target the enhancement of liveability and quality of urban environments. The most common type of liveability objective identified is residential privacy and views measured by distance [29,32,42,64,73,75]. Two articles optimised the distribution of public spaces to maximize their accessibility to improve urban liveability [31,48]. Similarly, three other articles optimised the distribution of urban green spaces as amenities for residents [28,39,45].

3.2. Model Types

This review identified four primary types of models used: (i) raster models, (ii) network models, (iii) polygonal models, and (iv) 3-dimensional (3D) geometric models. As every optimisation problem requires both objectives and models, the articles discussed in this section are the same 57 articles discussed in Section 3.1. Table 3 summarizes the model type, optimisation algorithm used, and data represented in each article. Articles in Table 3 listed in more than one category of model type are labelled with an asterisk. The analysis below presents the prevalence and application of each model type in contemporary research on UDO.

Overall analysis of the different spatial models demonstrated the growing prevalence of 3D models in UDO studies, with a total of 35 (44%) articles identified to have utilized 3D models. 3D models maintained the highest usage rate in nine out of the ten years studied and accounted for more than half of the studies from 2020 to 2022 (Figure 3). In many of the reviewed papers, 3D models provided additional means of evaluating an urban design via environmental simulation. Two studies combined 3D models with urban network models to generate more comprehensive urban designs [55,57]. The small number of studies incorporating multi-spatial models indicates that this is an underexplored research area within the UDO field, which is further discussed in Section 4.1. Furthermore, despite the significant percentage of complex 3D UDO models identified, none incorporated 3D representations of land topography in design optimisation.

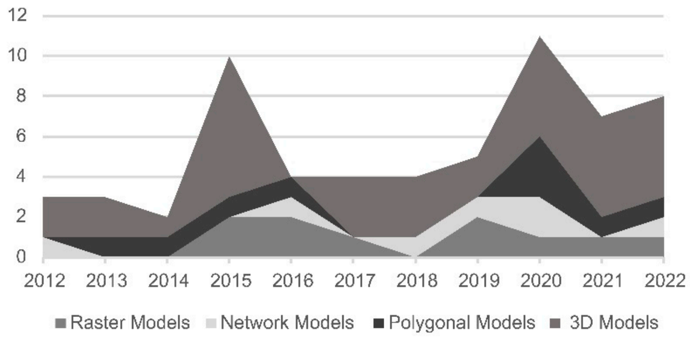


Figure 3. Histogram per model type.

Our review also demonstrates that UDO goals, as categorized in the previous section, are associated with specific model types. The model type and UDO goals of each of the reviewed articles are cross-tabulated in Table 4. It is worth noting that the total sum of the values in Table 4 does not equate to the total number of articles due to the consideration of repeated articles that addressed multiple goals. Most articles use 3D models when targeting outdoor comfort, natural resource, and liveability, with counts of 16 (20%), 15 (19%), and 9 (11%), respectively. While density goals are addressed with all types of models, all network models identified address the density goal. Results from this cross-tabulation emphasize the need for more research utilizing multiple model types and the need for methods to support multi-modal optimisation for research in UDO to address a wider range of planning goals.

Table 3. Model types and optimisation methods utilized in reviewed articles. Articles with optimisations applied to multiple model types are labelled with an asterisk.

Author, Date	Algorithm	Representation	LOD1	LOD2	LOD3
		Raster Models			
Caparros-Midwood et al., 2015 [28]	SA	Multiple risk indices			
Zhang et al., 2015 [37]	PSO	Urban boundary			
Mohammadi et al., 2016 [39]	LLTGRGATS	Land use			
Tong, 2016 [40]	GA	Building distribution			
Ma et al., 2017 [44]	Modified ACO	Urban boundary			
He et al., 2019 [51]	GA	Land use			
Yao et al., 2019 [53]	Gurobi	Fire risk index			
Tang et al., 2020 [58]	ACO	Urban boundary			
Genre-Grandpierre et al., 2021 [62]	Optidens	Speed index			
Xie et al., 2022 [76]	MLNN	Temperature based index			
		Network Models			
Delmelle et al., 2012 [20]	SA	Roads and bus stops			
Koenig & Varoudis, 2016 [38]	EA	Roads			
Yao et al., 2018 [49]	ACO	Roads			
Zhong et al., 2019 [54]	FICO Xpress	Roads, transport & job nodes			
Düring et al., 2020 [55] *	SPEA-2	roads & transport			
Koenig et al., 2020 [57] *	EA	Roads			
Lima et al., 2022 [72]	NSGA-2	Pedestrian paths			

Table 3. *Cont.*

Author, Date	Algorithm	Representation	LOD1	LOD2	LOD3
Polygonal Models					
Chee & Janssen, 2013 [23]	GA	Building footprint			
Haque & Asami, 2014 [27]	GA	Cadastral land use			
Wang & Guldmann, 2015 [36]	Gradient Descent	Cadastral land use			
Zhang et al., 2016 [41]	GA	Cadastral land use			
Düring et al., 2020 [55] *	SPEA-2	roads & transport			
Koenig et al., 2020 [57] *	EA	Cadastral plots & building footprints			
Wang et al., 2020 [79]	GA	building footprint			
Zhuang & Lu, 2021 [68]	GA	Facility distribution			
Martínez-Bernabéu & Casado-Díaz, 2022 [74]	GEA	Building footprint			
3D Models					
Gerber et al., 2012 [21]	GA			x	
Kaushik & Janssen, 2012 [22]	EA			x	x
Chen et al., 2013 [24]	EA			x	x
Choo & Janssen, 2013 [25]	EA		x		x
Choo & Janssen, 2014 [26]	EA		x		x
Conti et al., 2015 [29]	NSGA-2			x	x
Doe & Aitchison, 2015 [30]	SPEA-2			x	x
Makki, 2015 [31]	SPEA-2		x		
Koenig, 2015 [32]	Aforge GA library		x		
Si & Wang, 2015 [33]	GA		x		x
Taleb & Musleh, 2015 [34]	GA		x		x
Vermeulen et al., 2015 [35]	EA		x		x
Chen & Janssen, 2017 [42]	NSGA-2		x		
Juan et al., 2017 [43]	RSM		x		
Zhao et al., 2017 [45]	Greedy algorithm			x	
Bizjak et al., 2018 [46]	GA		x		x
Du et al., 2018 [47]	GA		x		
Makki et al., 2018 [48]	SPEA-2			x	
Du et al., 2019 [50]	NSGA-2			x	
Javanroodi et al., 2019 [52]	GA		x		x
Düring et al., 2020 [55] *	SPEA-2		x		
Kaseb et al., 2020 [56]	GA + PSO		x		
Koenig et al., 2020 [57] *	EA		x		
Wang, 2020 [59]	SSIEA			x	
Zhang et al., 2020 [61]	SPEA-2		x		x
Shirzadi & Tominaga, 2021 [63]	ESEA		x		
Wang et al., 2021 [64]	NSGA-2		x		x
Wu et al., 2021 [65]	GA		x		

Table 3. *Cont.*

Author, Date	Algorithm	Representation	LOD1	LOD2	LOD3
3D Models					
Wu et al., 2021 [66]	SAEA		x		
Zhao, 2021 [67]	ANN + GA			x	
Duering, 2022 [69]	SPEA-2		x		
Kaseb & Rahbah., 2022 [70]	PSO + GA		x		
Li et al., 2022 [71]	GA		x		
Ma & Ameijde, 2022 [73]	GA			x	
Showkatbakhsh & Makki, 2022 [75]	NSGA-2			x	

Ant Colony Optimisation (ACO); Artificial Neural Network (ANN); Evolutionary Algorithm (EA); Enhanced stochastic EA (ESEA); Genetic Algorithm (GA); Multi-Layer Neural Network (MLNN); Non-dominated Sorting GA (NSGA); Low-Level Teamwork Greedy Randomized Adaptive Search Procedure (LLTGR); Particle Swarm Optimisation (PSO); Response Surface Methodology (RSM); Simulated Annealing (SA); Surrogate Assisted EA (SA-EA); Strength Pareto EA (SPEA); Steady Stage Island EA (SSIEA); Tabu Search (TS).

Table 4. Cross-tabulation of spatial models and urban goals in references.

Goals / Model Types	Natural Resource	Outdoor Comfort	Cost	Density	Liveability
Raster Model	1	1	3	7	2
Network Model	0	1	0	7	0
2D Model	0	2	4	7	0
3D Model	15	16	4	5	9

3.2.1. Raster Models

Raster models provide a means of spatial computation and representation by abstracting urban spaces as a grid of cells. This review identified 10 (13%) articles employing raster models for UDO. Common applications of raster models in UDO include the study of regional boundaries and land use types. For example, Ma et al. and Tang et al. [44,58] employed raster models to identify optimal urban growth boundaries. Optimising urban growth in relation to rural settlement has also been addressed with raster models [51]. Raster models have been used in several studies to optimise the distribution of urban spaces and facilities including green spaces [40], farmland zones [37], public service facilities [53], or mixed-land use [39]. Genre-Grandpierre et al. [62] optimised a raster model to obtain areas with maximum accessibility and minimum car speed. Caparros-Midwood et al. [28] conducted a multi-objective optimisation of a raster model for sustainable development. This study informed its evaluation criteria with six raster models: heat hazard, vulnerability, flood zone probability, accessibility, urban sprawl, and existing green spaces. Raster models are also used to train multi-layer neural networks for predicting outdoor mean radiant temperature [76].

3.2.2. Network Models

Network models are a mathematical representation of a set of objects (nodes) and linkages (edges). Network models have been used to represent transportation networks, land use planning, and other forms of urban connectivity, and are still in use today [80,81]. This review identified 7 (9%) articles that optimised urban network models with application to facility distribution [20], distribution of affordable housing [54], efficiency of travel [49], and efficiency of street network configuration [38,55,57,72].

3.2.3. Polygonal Models

Polygonal models depict spatial boundaries through vector data comprising coordinates for the polygon outline and additional attributes. A total of 9 (11%) of the reviewed articles utilized polygonal models for UDO, with 5 representing cadastral land plots and 4 representing building footprints. Optimising land use allocation is found to be the most common application of polygonal models [27,36,74]. The second most common application of polygonal models is facility distribution optimisation, including healthcare facility sufficiency [41] and network station optimisation [60]. When used to represent building footprints, polygonal models are used in several studies to optimise building layouts [23,55,57] and the distribution of green spaces on building rooftops [68].

3.2.4. 3D Models

Three-dimensional (3D) models are defined for the purposes of this review to include any type of model that spatially represents three-dimensional forms, including mesh and non-uniform rational B-spline (NURBS) models. Among the reviewed UDO studies, 35 (44%) utilized 3D models. For the purposes of tabulation and comparison, we further categorised 3D models for UDO according to their level of detail (LOD) as either simple vertical extrusions (LOD1), more complex 3D solids (LOD2), or detailed 3D models including building façade information (LOD3).

3D extrusion models (LOD1) are implemented in 23 (29%) of the reviewed UDO articles. The most widely associated goal of this type of model is outdoor comfort, with eight articles addressing only outdoor comfort [43,47,56,61,63,65,70,71], and six more articles addressing a combination of goals including outdoor comfort [31,34,55,64,66,69].

Complex 3D models (LOD2) are 3D models including cantilevers or sloped faces and are found in 12 (15%) of the reviewed articles. Eight of these employed this model type to permit geometry-based analysis, including shade optimisation from tree cover [45], profit maximization from mixed-use tower typology [21], optimised shading from neighbouring buildings [59], maximized shape for PV potential [67], optimised spatial configuration for view and construction complexity [73], optimised circulation for existing towers [75], and a more detailed analysis of outdoor comfort in comparison to extrusion models [48,50].

Finally, 13 (16%) of the reviewed articles are identified to have used detailed 3D models with facade information (LOD3). These LOD3 models are most often utilized for optimising natural resource goals [22,24–26,29,30,33–35,46,52]. Separately, LOD3 models have been used to study outdoor comfort during winter [61] and liveability with sky view ratio from windows [64].

3.3. Generative Modelling Techniques

In the context of UDO, generative models generate new spatial design solutions based on input parameters. While all research into UDO used generative models, only 11 (14%) of the reviewed articles presented the setup of the generative model in greater detail (Table 5). The range and accuracy of generative models directly impact the application of UDO results to practice, as meaningfully expanding the design space supports better-informed decision-making.

The articles discussed in this section propose novel methods for automatically generating urban spatial models for subsequent optimisation, such as generating building typologies or road networks. While many of the reviewed works address the generation of urban geometries (boundaries, road networks, building footprints), also included are articles that propose methods of generating non-geometric model attributes, for example by tagging models with materials.

Multiple articles presented generative models for typical residential building typologies, including low-rise block typologies [33,34,82,83] and high-rise towers [42,73,79,84]. Lima et al. [72] developed a generative urban network model and Koenig et al. [57] combined a generative urban network and a 2D polygonal spatial model.

Table 5. Generative modelling techniques in references.

Author, Date	Description
Si & Wang, 2015 [33]	Low-rise housing model for unit allocation
Taleb & Musleh, 2015 [34]	Urban-scale, single-story housing model with a basic façade for heat gain.
Chen & Janssen, 2017 [42]	Automatically parametrize city models with orientation and height parameters
Koenig et al., 2020 [57]	Integrated geometry model for road networks, parcels, and buildings.
Osintseva et al., 2020 [83]	Urban block morphology model
Wang et al., 2020 [79]	Single high-rise morphology model
Natanian et al., 2021 [82]	Simple urban block morphology model for solar analysis.
Lima et al., 2022 [72]	Exploratory urban street network model.
Ma & Ameijde, 2022 [73]	Single high-rise morphology model with construction constraints
Wang, 2022 [84]	Single block morphology model.

3.4. Optimisation Methods

Various optimisation algorithms can be implemented in UDO methodologies. However, results from Table 3 show that there is an overwhelming preference for metaheuristic-based algorithms. In total, 50 of the reviewed articles (87.7%) employed metaheuristics, including modified versions of genetic algorithm (GA), evolutionary algorithms (EA), particle swarm optimisation (PSO), ant colony optimisation (ACO) and simulated annealing (SA). This proves that metaheuristics remains the most widely used school of algorithms. Like other global, derivative-free optimisation methods, metaheuristics do not require the user to define mathematical expressions and are indifferent to solution space convexity and continuity, making them applicable to all problem types and easy to use for UDO. In tabulating all optimisation algorithms used in the reviewed articles, we found that 16 (20%) and 7 (9%) used GA and EA in their work, respectively. A further 21 articles utilized modified variations of EA and GA, including NSGA-2, Aforge GA, ESEA, SA-EA, SPEA, SPEA-2, and SSIEA. Separately, 8 (10%) articles used other metaheuristics such as variations of ACO, PSO, and SA. Amongst these, two articles applied optimisation using a hybridized GA and PSO [56,70]. Additionally, Koenig [32] utilized a toolkit of genetic algorithms packaged as Aforge GA Library to further increase the accessibility of these algorithms for UDO and other applications.

A notable deviation from metaheuristics is presented by Brunetti [85], who proposed a Cyclic Overlapping Block Coordinate Search (BCS) method and seven metrics to evaluate the exploratory power of the proposed algorithm (e.g., solution quality, search quality, net search size, etc.). However, as no results from design optimisation or comparative studies are presented in the article, it is excluded from Tables 1 and 3.

The reviewed articles present a variety of approaches to setting up multi-objective optimisation (MOO) or single-objective optimisation (SOO) for urban design problems. Two articles employ MOO to simultaneously optimise three urban goals simultaneously. Koenig et al. [57] applied evolutionary MOO to optimise both street network geometry and building footprints on land parcels. While MOO addresses more complex results due to data with higher dimensionality, the added complexity can be addressed by formulating the MOO as a weighted SOO problem using scalarization [86]. Linear scalarization minimizes the sum of objective functions (f) with assigned weights (w) for a solution (x) within a design space (X) (See Equation (1)). Optimisation results from scalarized SOO will converge faster relative to MOO [87].

$$\text{minimize} \sum_{i=1}^{m} w_i f_i(x), x \in \mathrm{X} \tag{1}$$

Four of the reviewed articles performed a comparative analysis of multiple optimisation algorithms (Table 6). Two authors compared evolutionary-based algorithms [37,70]. Wortmann [88] demonstrated that model-based solvers, which are methods that iteratively refine a model during optimisation to be used for heuristic searches, such as RBFOpt, outperform many metaheuristic solvers in performance and robustness by benchmarking eight different algorithms on seven problems. Mohammadi [39] argued that hybridizing multiple optimisation algorithms would improve the efficiency of the algorithm.

Table 6. Articles comparing various algorithms for UDO problems.

Author, Date	Description	Algorithms (Ranked by Author)
Zhang et al., 2015 [37]	Scalarized SOO for compactness, soil fertility, and transportation cost.	(1) Dynamic hybrid swarm of particle swarm optimisation (DHS-PSO) (2) Genetic algorithm (GA) (3) Particle swarm optimisation (PSO)
Mohammadi et al., 2016 [39]	Scalarized SOO for land use.	(1) Low-level teamwork-Greedy Randomized Adaptive Search Procedure-Genetic algorithm-Tabu search (LLT-GR-GA-TS) (2) Single-valued neutrosophic set (SVNS)
Wortmann, 2019 [88]	SOO for two structural (weight), three energy (annual energy consumption), and two daylight (useful daylight illuminance) problems.	(1) Opt. w Radial basis function (RBFOpt) (2) Controlled random search (CRS2) (3) Direct search algorithm (DIRECT) (4) PSO (5) SA (6) Covariance matrix adaptation evolution strategy (CMAES) (7) GA (8) Simple GA (SGA)
Kaseb & Rahbah., 2022 [70]	SOO for wind-based pedestrian comfort.	(1) Hybrid GA-PSO (2) PSO (3) GA

3.5. Surrogate Models

Surrogate model integration with UDO is a recent area of research that leverages new machine learning methods to accelerate optimisation. Surrogate models, sometimes referred to as meta-models and grouped under hyper-heuristics, replace costly simulations or calculations with quick approximations [89]. This review distinguishes between two types of surrogate models: online and offline.

Online surrogate models are refined during the search by updating the approximated fitness landscape with every new solution generated. The RBFOpt algorithm is an example of an online surrogate model, which has been applied to the optimisation of architectural design [90]. Mao [89] presented an online hyper-heuristic EA that optimises the calibration of an urban microclimate model to match measured conditions.

Offline surrogate models, or pre-trained surrogates, are trained from a large set of labelled data beforehand. Offline surrogate models were identified in 12 (15%) of the reviewed UDO articles (Table 7). After training, the offline surrogate can be implemented within the UDO workflow to replace the slow simulation and accelerate optimisation. Although offline surrogate creation depends on simulation software to create the samples for model training, there is no discernible preference among the reviewed papers for a specific simulation software (Table 7). Validation of the offline surrogate model is accomplished in 10 out of 12 articles using the same simulation software used for training. Only two articles cross-validated the simulated results with either onsite measurements [43] or benchmark datasets [50]. Artificial neural networks [46,64,67,76] and response surface methodology [47,50,65] are the most widely used methods for training surrogates. Waibel [91] evaluated six different regression methods and reported that all methods behaved similarly. Notably, Düring [55] conducted a test using image-to-image conditional adversarial networks to predict a false-colour raster image of wind and solar simulation based on a grey-scale height map of an urban area. Although the pre-trained model by Düring took several months to train, the resulting model can subsequently be used in a UDO workflow to make quick and accurate estimates. In an extension of the single surrogate workflow, Wu [66] proposed a method to use two surrogates during optimisation for global and local searches, respectively.

Table 7. Articles using pre-trained surrogate models in UDO.

Author, Date	Simulation Package	Validation	Method to Train Surrogate
Juan et al., 2017 [43]	ANSYS/Fluent	Measured w wind velocity meter	MVR
Bizjak et al., 2018 [46]	EnergyPlus	Same software	ANN
Du et al., 2018 [47]	Detached Eddy Simulation	Same software	RSM
Du et al., 2019 [50]	Not specified	Benchmarked w CEDVAL B1-1	RSM
Düring et al., 2020 [55]	Ladybug, OpenFOAM	Same software	CAN
Waibel et al., 2021 [91]	OpenFOAM	Same software	RF, GP, LR, KNN, DT, SVR
Wang et al., 2021 [64]	QuVue, Eddy3D	Same software	ANN
Wu et al., 2021 [65]	ANSYS/Fluent	Same software	RSM
Wu et al., 2021 [66]	Phoenics	Same software	GP + GBRT
Zhao, 2021 [67]	Ladybug	Same software	ANN
Li et al., 2022 [71]	ASLUM v4.1	Same software	GPR
Xie et al., 2022 [76]	Not specified	Same method	ANN

ANN: Artificial Neural Network; CAN: Conditional Adversarial Networks; DT: Decision Trees; GP: Gaussian Process; GBRT: Gradient Boosted Regression Tree; KNN: K Nearest Neighbours regression; LR: Linear Regression; MVR: Multi-Variate Regression; RF: Random Forest; RSM: Response Surface Methodology; SVR: Support Vector Regression.

3.6. Solution Space Exploration

UDO can result in too many solutions, which requires further computational analysis to aid in user selection. The task of exploring UDO solutions is referred to as solution space exploration (SSE). SSE supports multi-objective design optimisation where conflicting objectives may result in a range of Pareto-efficient solutions that become difficult to visualize as the number of objectives increases. Solution space exploration for UDO is an explicitly socio-technical area of research, as it combines the visualization of large multi-dimensional data sets with supporting an end user's goals for the design process. Urban designers may also wish to explore viable solutions beyond the Pareto-efficient solutions to better understand the design model, or to select results meeting additional and/or non-quantitative criteria. We discuss three subcategories of SSE below (Table 8), with key figures from the cited papers included in Figures S1–S10 in the Supplementary Materials for easier reference.

Visual methods of solution space exploration for UDO focus primarily on presenting multi-dimensional (multi-parameter or multi-objective) results with greater clarity for users. Heinrich and Ayres [92] proposed an exhaustive visualization method that captures the evolution of results over time during optimisation. Wortmann [93] extended the widely used star coordinate plot by introducing a heatmap generated using a surrogate model trained on explored solutions. Heusinger and Sailor [94] extended the wind rose map, introducing hot and cold wind roses to represent temperature changes across seasons. Petroc and Wortmann [95] introduced the use of autoencoders, a concept from machine learning, to reduce the dimensionality of UDO solution space.

Articles on interactive dashboards for UDO have addressed design processes and user experience as part of their research. Conti et al. [29] supported the user in selecting and comparing pairs of Pareto front visualizations along with an exhaustive visualization of the sampled Pareto solutions. This approach combined a general overview of the solution space with user-defined targeted sampling. Makki et al. [48] presented an SSE dashboard that accompanies a 3D solution visualization with scaled visualizations of the solution fitness for each objective. Duering et al. [69] introduced a dashboard that allowed users to toggle between various methods of SSE, including visualizations using parallel coordinate plots, dimension reduction algorithms, clustering, and regression.

The introduction of additional machine learning methods to improve SSE efficiency or user understanding is increasingly prevalent in UDO studies. Autoencoders, clustering algorithms, regression, and principal component analysis can be incorporated into an interactive dashboard to support a deeper understanding of the solution space by analysing for patterns and trends [44,95,96]. The solution selection framework proposed by Showkatbakhsh and Makki [75] is distinctive in its presentation of a stepwise method of supporting a solution selection process they described as at least partially subjective. They prioritized identifying (i) the clustered Pareto set from all generations, (ii) the most optimal results from each objective, (iii) the solution closest to the utopia point, and (iv) solutions that address all objectives equally. Additionally, conducting meta-level analysis (analysing how a user explores) and managing design information with the appropriate data structure can allow users to reiterate past solutions and make more optimal decisions [96,97].

Table 8. Methods for solution space exploration.

	Author, Date	Description
Solution Space Visualization	Heinrich & Ayres, 2016 [92]	Squarified treemap.
	Wortmann, 2016 [93]	Heatmap overlay on star coordinate plot.
	Heusinger & Sailor, 2019 [94]	Spatial map of wind rose analysis.
	Petrov & Wortmann, 2021 [95]	Autoencoder maps many variables into 2 dimensions.
Interactive Dashboards	Conti et al., 2015 [29]	Pareto front paired with 3D solution view.
	Makki et al., 2018 [48]	Each visualized solution is accompanied by smaller maps for every objective.
	Duering, 2022 [69]	Dashboard with submenus for PCP, dimension reduction, clustering, and regression.
ML for Solution Exploration	Izakian et al., 2016 [96]	Solution clustering based on trajectories.
	Lee et al., 2019 [97]	Propose a structure to iterate across different 'design episodes' across one 'design session'.
	Showkatbakhsh & Makki, 2022 [75]	Framework to fine-tune from commonly requested solution subset.

3.7. Optimisation Frameworks

With multiple steps and models required for UDO, some articles have proposed novel optimisation frameworks to clarify the process. These optimisation frameworks clearly define the steps of their process using a flowchart and typically involve a combination of automated and human-controlled actions. This combination of computational and human actions is addressed as "Cognitive Design Computing" [98]. The increasing need for multiple models drives the need for frameworks to address multi-modal data. Finally, the introduction of cloud computing and Web App development for UDO has increased interest in frameworks to detail the flow of data across local or remote computing environments and software used.

Optimisation frameworks are used in several of the reviewed articles to define human–computer interactions in UDO research and software used. Diagrams of frameworks from the cited works discussed in the following paragraphs can be found in Figures S11–S17 in the Supplementary Materials. A two-loop framework is presented by Chen et al. [24], where a human decision-making loop including schema formulation and data analysis incorporates an inner loop of computational evaluation and optimisation. Singh and Gu [99] proposed a similar concept, visualized as implicit and explicit links between key steps in design optimisation. Koenig and Schmitt [98] expanded a framework to four connected domains: (i) user interaction domain, (ii) geometry domain, (iii) learning domain, and (iv) data analysis domain. Their framework advances a thesis that machine learning models (grouped under learning and data analysis domains) can mediate between the human user and the back-end operations of an urban model. Users can easily select various optimisation solvers and evaluation models to use from a predefined model container. Finally, the authors describe how a model of user preferences, i.e., an 'estimation of the user's goals,' further informs the process of evolutionary optimisation.

Methods for working with multiple models in the UDO process are also articulated in several published frameworks. Complex urban environmental optimisation incorporates multiple analytic models often in consecutive phases. Mirzabeigi and Razkenari [100] define a multi-phase optimisation framework evaluating a building energy model and an outdoor comfort model. Fuchkina et al. [101] advance a modular optimisation framework that defines three distinct levels (strategy, processing, and instance) that correspond to consecutive steps of narrowing solution exploration with different analytic techniques and user interactions defined at each level. Following a similar process of narrowing, Shirzadi and Tominaga [63] propose a multi-fidelity optimisation framework where analysis is initially conducted with lower resolution models (faster, less accurate) followed by increasingly higher (slower but more accurate) resolution models. Mueller et al. [102] provide one of the earliest instances of an optimisation framework integrating both local and cloud-computing modules using Microsoft Azure. In this case, the framework describes a system for passing computationally expensive analysis to a cloud service within an optimisation process.

4. Future Directions

Our review indicates that there is a need for future research to better address UDO as a complex socio-technical problem spanning a wider range of planning goals and encompassing multiple human and machine actors working in tandem. The reframing of UDO as a socio-technical research project raises new research directions, aiming not just at generating the best solutions, but at generating the best solutions for specific stakeholder interests. UDO, construed in this manner, is an area of transdisciplinary research, which would seek to support the 'mutual learning of science and society' [103]. Four areas for future work in UDO are presented below: (i) methods of optimising across multiple models (Section 4.1), (ii) exploration of frameworks for scenario building and backcasting (Section 4.2), (iii) interfaces that address a multiplicity of stakeholders (Section 4.3), and (iv) advancing AI applications for UDO, including generalizable surrogates and user preference learning (Section 4.4). Our descriptions of areas of future work in UDO are developed based on research gaps and trends observed in the literature review and argued with reference to the reviewed works.

4.1. Integrating Multiple Design Models

Supporting urban planners as they build holistic proposals across multiple goals and model types presents a first socio-technical challenge to current research on UDO. Our review of UDO model types (Section 3.2) showed that research integrating multiple model types is lacking. Optimisation for multiple urban goals is also found to be less frequent in reviewed works than single-goal optimisation. Only two works were identified that optimised across multiple model types [55,57]. Our review has not identified any studies that incorporate counter-modelling, i.e., the use of multiple models to test for the same objective [13]. These types of multi-model multi-goal studies would better assist planners in understanding the potential biases or inaccuracies of UDO (in the case of counter-modelling) or addressing urban planning more holistically across the scales of land-use planning, network layout, and density distribution.

To address complex model interactions and solutions generated by multi-model, multi-goal optimisation, improved methods of SSE for UDO are needed. Research on SSE for UDO has devoted its attention primarily to multiple objective problems, with comparatively little attention to the problem of searching across multiple models. Future research could test methods for users to add or modify existing aspects of an optimisation model, producing greater result diversity, instead of a single optimal solution [104]. Work on the visualization of multi-dimensional solution space [93], interactive solution dashboards [48], and intelligent solution recommendations [96] can all potentially be extended to multiple models in future research. Multi-model solution space exploration could, for example, assess related performance criteria across multiple model scales or permit reasoned comparison across competing model outputs (i.e., counter-modelling). As the real-world workflows of urban planners require many iterations across a variety of scenarios, UDO research may also seek to develop a better capacity to rigorously define scenarios via model set-up and compare across the multiple resulting solution spaces.

4.2. Adapting Optimisation to Support Scenario Building and Backcasting

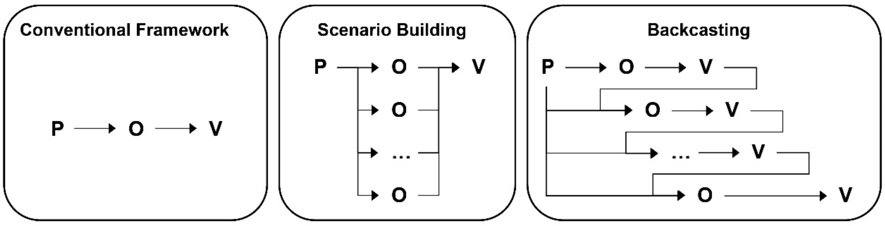
While scenario-building workflows for UDO become increasingly relevant as researchers seek to optimise across multiple model types and goals, little contemporary research has elucidated how computational optimisation can support decision-making frameworks for city planning. Scenario building is used by planners to account for future uncertainty by defining multiple plans that respond to potential future conditions [105]. Scenario building in the context of UDO implies that multiple sets of optimisations are conducted, each addressing differing sets of objectives that are adapted to reflect future conditions targeted by planners. To support the capacity of UDO to engage in scenario building would require the development of methods to model future conditions for different objectives in a planner-led exploration process. Solution exploration across multiple optimisation results sets would also be necessary.

Backcasting, a planning process targeting large-scale goals through multiple sequential steps, is a further city planning process that future research on UDO may seek to develop. Backcasting can be conceptualized within the context of UDO research as the sequential optimisation of a series of interlinked models that collectively elucidate the best pathway for addressing a complex urban challenge. Koenig and Schmitt [98] notably identified backcasting as a desired capability for future UDO systems. Their 'cognitive design computing framework' combined user interaction and user preference learning to allow the planner to change goals and model features during a backcasting process. The authors' emphasis on a user-guided methodology is reinforced by contemporary definitions of backcasting in planning, which emphasize incorporating a wide range of users in efforts to support higher-order learning and build consensus on planning goals and outcomes [106].

For UDO to effectively contribute to backcasting, the technical capability of generating and searching across sequentially developed scenarios (a data structure problem) must be accompanied by an ability to convey information to and receive feedback from a variety of stakeholders. The nested data structure used by Koenig et al. to tackle both land subdivision and building generation is one of only a few published examples of this type of data structure [57]. Future research on the application of knowledge graphs to UDO can support improved user understanding of complex scenario-building processes that incorporate both algorithmic optimisation and decision-making by multiple human actors. Currently, data structures have been used to represent city modelling [107,108], but have yet to convincingly incorporate data on the actions taken by the human actors to achieve the resulting design.

To illustrate how UDO can contribute to scenario building and backcasting, this research defines three schematic frameworks describing the flow of data between models and users in these applications (Figure 4). In a conventional optimisation framework for

UDO, a single model is defined and solved linearly (Figure 4, left). UDO for scenario building compares results generated by multiple optimisation definitions, using different constraints, parameter ranges or different sets of models to provide a range of scenarios (Figure 4, middle). Finally, UDO for backcasting is schematized as involving sequential optimisation of multiple inter-dependent or nested optimisation models (Figure 4, right).



P Problem definition process
O Optimisation and model building process
V Visualisation, analysis and interaction process
→ Dataflow

Figure 4. Optimisation frameworks for UDO.

4.3. Platform for Addressing Many Stakeholders

Our review demonstrates the extent to which UDO research remains a technically oriented field, with user interaction, experience, and understanding addressed only by a small subset of articles covered mainly under the solution space exploration above [28,95–97]. To contribute to holistic planning practices, however, the ability to accommodate a wider range of stakeholders as users of UDO will be an important future research area for the field. The rapid development of commercial web-based tools for UDO between 2018 and 2022, including Sidewalk Labs' Delve and Autodesk's Spacemaker, emphasizes the growing importance of web-based tools for UDO [7]. However, as these commercial tools are under commercial licenses and are unavailable to the authors of this research, the tools cannot be evaluated for their effectiveness for UDO. Furthermore, as these tools primarily target the real estate industry, they remain expert-oriented, with limited relevance to more broadly participatory planning processes and academic research. Future UDO research may seek to overcome these gaps by developing more broadly participatory tools and conducting user studies to ascertain patterns of use and success metrics for inclusive UDO. As site simulation in the form of web tools can accumulate a dataset of user interaction, it is foreseeable that future research will use this data to build predictive models of user preference in UDO. Participatory, web-based UDO research will overlap with domains of human–computer interaction (HCI), user experience and interface design (UI/UX), as well as with work on explainable AI (XAI) [48,109].

4.4. Integrating AI Models into UDO

Our review indicates that AI is an increasingly integral component of UDO methodologies, especially for surrogate modelling and solution space exploration. With the increasing number of objectives, models, and iterations considered in UDO research, AI methods for enhanced solution space exploration are likely to continue to grow as a research area.

Surrogate models have been shown to improve the optimisation process by replacing long, detailed simulations with fast approximations (Section 3.5). These include offline surrogate models, detailed in Table 6, which are trained by large datasets of mostly synthetic data (digital simulation results), but also online surrogate models that are trained in real-time on simulated data generated during the optimisation process [110].

Future research in AI integration with UDO will likely expand work on generalizable surrogate models. While surrogate models have demonstrated their effectiveness in early-stage design, they cannot be applied across multiple UDO studies if these are overly specific to a given context or overfitted to their training data [64,67]. Future work can expand on generalized surrogate models that can reliably predict simulation results from multiple parametric design models using varying sets of parameters. This may be achieved by replacing site or building design parameters with spatial parameters instead.

Preference learning models, such as automated classifiers trained on user preference data, are an additional area of AI integration with UDO that has received only limited attention in research thus far [111]. While Koenig and Schmitt [98] proposed a 'learning' module in their cognitive design computing framework that could inform the optimisation process with a model of user interactions, few published works have subsequently addressed this topic. More research is needed to understand the technical methods required for incorporating preference learning in UDO. Initial work in this area has been advanced for user preference measuring and prediction in urban design interfaces [112] but not within a design optimisation framework. Several commercial UDO tools also demonstrate preference learning as part of results recommendation interfaces but with limited published information on their technical methods [7]. Future work on preference learning in UDO systems must also consider the ethical and bias concerns now commonly associated with AI models [113] but with new implications for design and decision-making in urban spaces.

5. Conclusions

UDO shows great promise in improving understanding of the complex design challenges of contemporary city planning. This paper presents a systematic review of UDO research to highlight key opportunities for improved criteria definition, model integration, and stakeholder-relevant solution exploration. Close analysis of UDO-related articles published from 2012 to 2022 is conducted across seven categories, including optimisation goals, model types, generative techniques, optimisation methods, surrogate models, solution space exploration, and optimisation frameworks. We observe that there is an existing gap in accommodating multi-model, multi-goal optimisation and an ongoing trend towards the use of AI and ML techniques. The results of the review emphasized that contemporary challenges for UDO are not only technical but also social. Socio-technical challenges for UDO discussed include (i) delivering understandable results to users in complex solution space exploration and (ii) integrating intuitive user controls into automated UDO frameworks.

Building from the identified research gaps, trends, and challenges described in the review, four future directions for research are described: (1) developing frameworks to integrate multiple design models will ensure that UDO sufficiently addresses the multidisciplinary work of urban planners; (2) adapting optimisation to support scenario building and backcasting will assist planners with a computational framework that aligns with advanced planning processes; (3) implementing UDO on a more accessible platform will allow for a higher level of collaboration with stakeholders and improved interactions; and (4) integrating AI models, including surrogate modelling and preference learning methods, will improve the efficiency of planners using UDO. The future directions described for UDO research in this review would better support evidence-based urban design for planners, policymakers, designers, and residents alike.

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