AUTOMATED SEMANTIC SWOT ANALYSIS FOR CITY PLANNING TARGETS

Data-driven solar energy potential evaluations for building plots in Singapore

AYDA GRISIUTE[1], ZHONGMING SHI[2], ARKADIUSZ CHADZYNSKI[3], HEIDI SILVENNOINEN[4], AUREL VON RICHTHOFEN[5] and PIETER HERTHOGS[6]

[1,2,4,5,6] Singapore-ETH Centre, Future Cities Lab Global Programme, CREATE campus, 1 CREATE Way, #06-01 CREATE Tower, Singapore 138602.

[3] CARES, Cambridge Centre for Advanced Research and Education in Singapore, Singapore.

[5] Arup, Berlin, Germany.

[1]ayda.grisiute@sec.ethz.ch, 0000-0001-7328-847X

[2,6]{shi, herthogs}@arch.ethz.ch, 0000-0002-3744-1649, 0000-0003-2562-8374

[3]arkadiusz.chadzynski@cares.cam.ac.uk, 0000-0001-8084-9474

[4]heidi.silvennoinen@sec.ethz.ch

[5]Aurel.von-Richthofen@arup.com, 0000-0002-8712-1301

Abstract. Singapore's urban planning and management is cross-domain in nature and need to be assessed using multi-domain indicators — such as SDGs. However, urban planning processes are often confronted with data interoperability issues. In this paper, we demonstrate how a Semantic Web Technology-based approach combined with a SWOT analysis framework can be used to develop an architecture for automated multi-domain evaluations of SDG-related planning targets. This paper describes an automated process of storing heterogeneous data in a semantic data store, deriving planning metrics and integrating a SWOT framework for the multi-domain evaluation of on-site solar energy potential across plots in Singapore. Our goal is to form the basis for a more comprehensive planning support tool that is based on a reciprocal relationship between innovations in SWT and a versatile SWOT framework. The presented approach has many potential applications beyond the presented energy potential evaluation.

Keywords. Semantic Web; Knowledge Graphs; SWOT Analysis; Energy-driven Urban Design; SDG 7; SDG 11.

1. Introduction

In Singapore, urban planning and management are done by multiple government

POST-CARBON, Proceedings of the 27th International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA) 2022, Volume 1, 555-564. © 2022 and published by the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA), Hong Kong.

agencies, implying that it is cross-domain in nature. This nature impacts how we measure, evaluate and understand the challenges the city is facing, such as climate change, the liveability of cities, or urban energy demand (Richthofen, 2022). Sustainable Development Goals (SDGs) is an effort to address these challenges and can support planners in comparing, monitoring and measuring the progress of planning strategies through the evaluation of diverse indicators (Massaro et al., 2020). However, such actions require the integration of heterogeneous data and flexible frameworks that enable a comprehensive evaluation of diverse SDG-related planning metrics. While relevant data have been made available through active digitalisation and improved storage capacities (Winkelhake, 2018), existing urban data formats and modelling techniques — such as GIS — remain relatively static and siloed. They lack standardised exchange formats, making it difficult to cross-reference, analyse or track changes (Chadzynski et al., 2021) and impede the integration of (big) data in planning tasks. Therefore, sustainable digitisation and innovation in city planning and knowledge management are essential for achieving SDGs (Massaro et al., 2020).

There is a need for more holistic analyses relating to SDGs that enable the evaluation of cross-domain urban indicators and metrics. Semantic Web Technologies (SWT) is a promising approach to address data fragmentation and improve interoperability by linking data and making it more connected and discoverable through Knowledge Graph (KG) platforms (Chadzynski et al., 2021). In addition, SWOT analysis framework (Strengths, Weaknesses, Opportunities and Threats) has proven to be a versatile and effective tool for strategic urban planning and the evaluation of cross-domain metrics for particular planning targets.

In this paper, we introduce an approach to automate the evaluation of multi-domain targets of city planning using KG, enabling flexible interaction with heterogeneous data and addressing interoperability issues hindering core aspects of sustainable digitalisation in city planning. We present the first steps towards a more comprehensive decision support tool, integrating a dynamic geospatial KG platform with the SWOT framework, resulting in automated multi-domain evaluations of SDG-related planning targets. The remainder of the paper is structured as follows. Section 2 presents the broader research scope and background, how SWOT framework and SWTs address the need for holistic urban analysis, and our use case — a SWOT analysis assessing on-site solar energy potential of plots across Singapore. Section 3 describes our methods for storing heterogeneous data in a KG, deriving planning metrics, and integrating it into the SWOT analysis. Section 4 presents the SWOT analysis results and potential benefits for planners, while Section 5 discusses the main contributions of SWOT and SWT integration, discovered limitations and future work.

2. Background

2.1. CITIES KNOWLEDGE GRAPH

Our work was done as a part of the Cities Knowledge Graph (CKG) research project – an example of a Semantic City Planning System (Richthofen et al., 2022). CKG is a pilot for a comprehensive knowledge management platform that applies SWT and KGs to address interoperability challenges between different urban knowledge domains in order to digitally support the synthesis actions at the core of city planning (e.g. building consensus among stakeholders), hence addressing SDG 11 — Sustainable Cities and Communities — targets.

The CKG uses SWT to store data on the Web, link it using ontologies, and write rules for handling data across applications. Ontologies account for shared formal vocabularies of domain concepts, instances, and relations (Akroyd et al., 2021) and enable computers to infer semantic relationships between heterogeneous data. KGs express data as a directed graph with concepts or instances as nodes and relations as edges, and can be used to formalise domain knowledge, such as urban energy, mobility or planning (Shi, et al., 2021), into semantic models. Finally, KGs hosted in graph databases, often referred to as triple stores with query endpoints, enable exploration and interaction with such semantic models by executing SPARQL query statements (W3C, 2013).

The CKG is a subsystem of a broader collaborative research effort to develop a general, all-encompassing and dynamic knowledge graph called The World Avatar (TWA) — TWA consists of multi-domain knowledge representation and an ecosystem of autonomous computational agents operating on it (Akroyd et al., 2021). The agents can support planning tasks by dynamically reconfiguring the KG architecture and importing, exporting, updating and analysing urban data.

2.2. SWOT ANALYSIS FRAMEWORK

A SWOT analysis is a cognitive process defining and evaluating the interrelations between different factors of an entity or phenomenon across four categorical descriptors: Strengths, Weaknesses, Opportunities, and Threats (Learned et al., 1965). Ghazinoory et al. (2011) associate Strengths and Weaknesses with internal factors — variables that are a part of the entity, and Opportunities and Threats with external factors — variables that are external but can still influence the entity. In the context of future-oriented tasks such as planning, we also consider the temporal dimension in SWOT where SW represent present conditions and OT future ones.

Although originally used in the business field, this framework has recently been rigorously applied in quantitative indicator-based evaluations in the planning domain (Comino & Ferretti, 2016; Ervural et al., 2018; White et al., 2015). In these examples, indicators are categorised into four descriptors based on stakeholder workshops or literature reviews and prioritised using hierarchical weighting methods by domain experts. Additionally, the SWOT framework is also suited for geospatial analyses. Camino and Ferretti (2016) integrated GIS in their indicator-based SWOT analysis for parks to create thematic maps visualising the distribution and extent of vulnerable, threatened or valuable park areas, informing regional park management strategies for optimal environment preservation.

2.3. USE CASE — ON-SITE SOLAR ENERGY POTENTIAL

In this paper, we combine the SWOT framework with our CKG to automatically analyse the on-site solar potential of building plots. As cities are one of the main energy consumers worldwide, such an analysis responds to the need to consider clean energy systems already during the master-planning stages and is an established planning target (Shi et al., 2017) for addressing SDG 7 — Affordable and Clean Energy.

An evaluation of a plot's solar energy potential is a transdisciplinary effort and involves a variety of cross-domain metrics and factors, covering building typology, land use, urban form, cooling demand and energy integration costs resulting in a variety of methods (Shi et al., 2021). Using methods that only evaluate individual metrics is not enough to assess solar energy potential due to interaction effects between features like site coverage, land-use ratio and orientation (Shi et al., 2021) and accounting for these interactions is difficult. In comparison, our approach expresses these interactions through linked data.

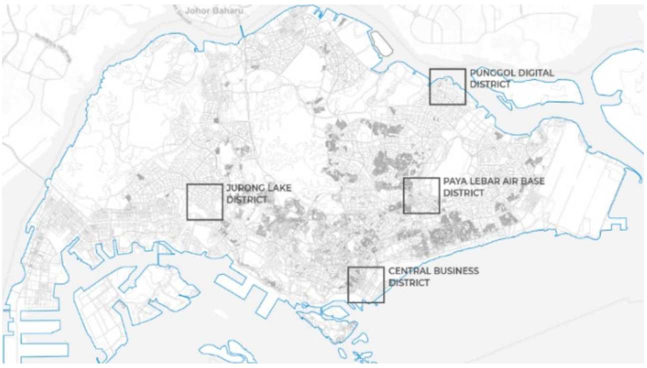

Figure 1 shows four chosen Key Growth Areas in Singapore, that aims to showcase integrated master-planning would benefit from solar energy potential considerations at early planning phases.

This paper builds on previous work (Grisiute et al., 2021), presenting an improved version of that automated SWOT analysis (improved metrics and score aggregation), now applied to diverse regions in Singapore. Singapore's 2019 master plan identifies several regions as Key Growth Areas (URA, 2021), with the aim to showcase how integrated master planning and technology could help create more liveable and sustainable cities in line with SDGs, including the integration of clean energy. Solar energy is the most feasible renewable energy source in Singapore, and will hence require the installation of more photovoltaic panels (Energy Market Authority, 2017). In order to do so, solar energy potential studies at early planning and urban design stages in these regions could prove to be very beneficial. As an experimental use case, we tested our SWT-based SWOT analysis in four of Singapore's Key Growth Areas: Punggol Digital District, Central Business District, Paya Lebar Air Base District and Jurong Lake District (Figure 1).

3. Methodology

3.1. STORING DATA IN THE CKG

We used open datasets from Singaporean government agencies (Data.gov.sg, 2021) and other planning-related datasets covering plot form, built form and land-use characteristics. First, we transformed these heterogeneous data to CityGML format with the Feature Manipulation Engine (FME). Second, we used our current CKG architecture — described by Chadzynski et al. (2021) — to transform flat geospatial

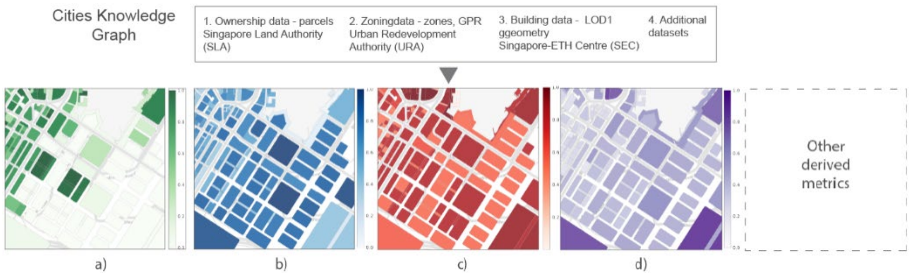

Figure 2 shows relevant metrics derived from datasets stored in the KG. Thematic gradient maps visualise each metric's value from highest (dark) to lowest (light): a) site coverage indicates to what extent the plot is covered by roof surface, which in Singapore is the most efficient for PV installation; b) elongation as measure for compactness that allows for efficient deployment of PV infrastructure; c) shading factor indicates how much buildings on plot are taller than its surroundings, which has direct effect on inter-intra shading; d) orientation metric indicates how much each plot deviates from recommended orientation for façade PV.

CityGML files into semantic triples and store them in the CKG. This graph database was structured using an ontology of the CityGML 2.0 standard called OntoCityGML (Chadzynski et al., 2021). Finally, the geospatial processing capabilities of the Blazegraph graph database instance used as the triple store enabled us to perform geospatial queries (Blazegraph, 2020).

3.2. DERIVED METRICS

Our SWOT analysis required metrics that measure particular characteristics of on-site solar energy potential as inputs. We derived these by executing manifold combinations of SPARQL queries against the CKG to retrieve each dataset's geospatial information (polygon geometries) and semantic information (zoning type, Gross Plot Ratio (GPR), building height). We linked the semantic information across datasets by comparing topological relations between the retrieved geometries. We then derived composite metrics that have a varying impact on on-site solar energy potential (Shi et al., 2021), like site coverage, land-use ratio, inter-intra shading factor and retrieved other relevant metrics, such as plot area, elongation and orientation, directly from the geometries (Figure 2).

3.3. SWOT ANALYSIS FRAMEWORK INTEGRATION

We included five of these metrics — site coverage, land-use ratio, plot orientation, elongation and shading factor — in our proof of concept evaluation of the solar energy potential of large numbers of building plots. As site coverage, plot orientation and elongation define the entity and are considered internal factors, their values were categorised as Strengths or Weaknesses (see also Section 2.2). Meanwhile, land-use ratio and shading factor values were linked to Opportunities and Threats, as these metrics define external context, but can still influence the plot. Refer to the cited papers for details on how each metric is defined.

- Site coverage | Extent to which the plot area is covered by roof surface, which is the most efficient location for PV installation in Singapore. Thus a high site coverage scores higher as it tends to increase roof PV possibilities (Shi et al., 2021).

- Land-use ratio | The average of the deviations from a recommended ratio of commercial and residential land uses of 30 to 70% respectively within the city block (Shi et al., 2021). Plots that are in city blocks with less deviation from the recommendation score higher.
- Plot orientation | The deviation from preferable east-west orientation for efficient facade PV installation (Shi et al., 2021). It is modulated by the plot area as an orientation has a stronger impact on plots with a small area, limiting design possibilities. Plots with lower deviation score higher.
- Plot elongation | Is expressed as the ratio between two circle diameters related to the plot: diameter of a circle with the same area as the plot and the diameter of the smallest bounding circle (Shi et al., 2020). Elongation is again modulated by the plot area (for the same reason as above). Smaller elongation tends to increase compactness allowing for efficient deployment of PV infrastructure.
- Shading factor | The difference between plot building height and average building height within a given radius. Plots with tall buildings have larger facade areas for PV installation and less risk for inter-intra shading (Shi et al., 2021) and thus score higher.

For the proof of concept, we normalised individual metric scores to a [0-1] range so metrics can be combined easily, with each metric contributing equally to the combined assessment. In reality, the importance or weight of different metrics varies; determining these variations is an operations research task that falls outside the scope of this paper. The metric scores were normalised between 0.0 and 1.0, where 1.0 represents the maximum value in the dataset and 0.0 is the minimum value. By default, we assigned normalised individual metric scores lower than 0.5 to W or T and scores higher than 0.5 to S or O. In this way, each metric was assigned to the SWOT categories for each plot. We computed a single S W O and T value per plot by aggregating results. Finally, analysis results were visualised in thematic gradient maps (Figure 3), presenting the geospatial distribution of the overall SWOT score, which is the difference between aggregated SO and WT, implying that in a positive overall score SO outweigh WT, and vice versa for a negative total score.

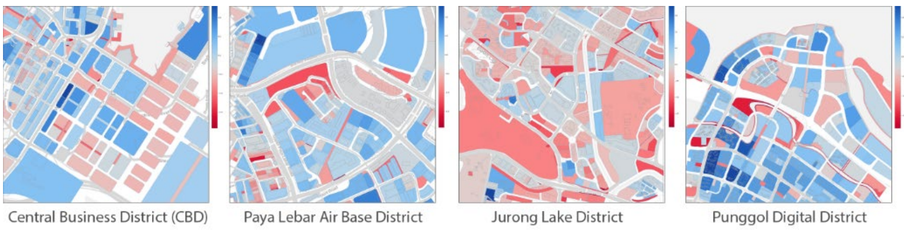

Figure 3 shows the geospatial distribution of overall SWOT analysis score across four chosen regions. Overall SWOT score is the difference between aggregated SO and WT. If positive, SO outweigh WT and are coloured in blue shades and, if negative, WT outweigh SO and are coloured in red shades. These maps show that our automated SWOT framework is consistent across cases with different topological features, development phases and information coverage.

4. Results

We applied our automated SWOT analysis to every plot in the aforementioned four Key Growth Areas in Singapore. The spatial distribution of overall SWOT scores in gradient maps (Figure 3) was instrumentally used to explore the solar energy potential of different plots. For example, parks, public spaces and small vacant plots scored lower across all locations due to the interaction between low site coverage and unsuitable land-use ratio that results in limited PV installation possibilities. Plots with east-west orientation and close to parks or public spaces scored higher due to interaction between desirable orientation, site coverage and shading effects.

To explore the relative contributions of each descriptor and individual metrics to the total score, we further investigated one region — Central Business District (CBD) (Figure 4b). From the thematic maps of four descriptors (Figure 4c) and a selected

Figure 4 shows one of the four regions SWOT analysis results: a) presents the score composition of four example plots; b) visualises the distribution of total SWOT analysis results; c) maps visualise the distributions of separate descriptors. Concentrations of S and O primarily consist of developed plots with high-rise buildings, while W and T cluster in areas that are not yet developed; d) displays a bar chart with SWOT results for all plots, showing that most plots balance negative and positive factors and that only very few plots are highly suitable or highly unsuitable for PV installation.

sample of plots (Figure 4a), we see that the interaction between orientation and elongation metrics (driven by a non-uniform grid urban structure) were main contributors to Strengths and Weaknesses determining varying plot performance. Plots that border water bodies or are used as pedestrian passages scored particularly low due to high elongation. The absence of buildings in this developing area had two implications: site coverage additionally contributed to the plot's Weaknesses, while shading factor contributed to Opportunities of those plots that are already built up. The majority of the plots have commercial land-use types which usually have higher energy use intensity, resulting in low land-use ratio scores and contributing to Threats. Finally, in our results, the majority of plots featured a balance between negative and positive factors, resulting in moderate solar energy potential and only very few plots were highly suitable or highly unsuitable for PV installation (Figure 4d) - at least in this unweighted multi-criteria assessment.

5. Discussion and Future Work

This paper presented a novel approach that integrates SWT, spatial analysis based on derived metrics, and a SWOT framework in order to support decision making in city planning. The benefits of this integration have been demonstrated through an experimental use case that shows how this method could be used to inform planners in SDG-related planning tasks. We emphasise that the main aim of this paper is to introduce a proof-of-concept of our automation approach, thus the type of evaluation and the specific scores resulting from our evaluation should be considered illustrative examples to demonstrate our KG-based automated SWOT analysis. The presented results demonstrate two main innovations of our approach.

First, planners could use generated maps to indicate potential plots for PV installations at the early master-planning level. The consistency of generated maps in Figure 3 shows that the automated SWOT framework can work across areas with varying topological features, information coverage or development stages. Thus, planners can apply this framework to a variety of sites and cases and even use it for the evaluation of on-site solar potential over time, as the features of an area change.

Second, the innovative value of the automated proof-of-concept approach stems from the ability to effectively combine heterogeneous linked data (derived metrics) with multidisciplinary expert knowledge (criteria evaluation and classification) into a single intuitive model (SWOT) — an ability that has been officially acknowledged as being inherently necessary for the successful implementation of SDGs (Massaro et al. 2020). The reciprocal relationship between metrics and automated evaluation opens new possibilities for SWOT analysis applications and provides a well-known interface (at least for urban planners) to interact with large semantic data stores, supporting decision-making. For instance, evaluating land use (e.g. mixed-use) developments in an automated way with more granulated linked data could facilitate and even augment land use classification tasks (Shi et al., 2021). Moreover, the malleable KG data architecture is designed for data to be updated, expanded or created with relative ease; such data architecture supports planning scenario generation and exploration, enabling the simulation of parallel worlds (Eibeck et al., 2020). We demonstrated that SWT and KGs enable planners to analyse cities through multi-domain indicators, as derived metrics used in the SWOT analysis would be challenging to develop based on individual datasets.

Despite the presented strengths, the work also has limitations. As the main aim of this specific SWOT analysis of solar energy potential is to illustrate our automation approach, the evaluation could be made more robust. The presented SWOT is limited by the choice of metrics, their uniform weighting, and different levels of granularity, and should therefore be considered a rough gauge for on-site solar energy potential assessment, primarily suitable for early-stage planning considerations. For instance, the low granularity of open zoning data poses challenges for computing an accurate land-use ratio. To make evaluation results more robust and informative, uniform metric weighting should be replaced by collaboratively determined and case-specific weights. The presented uniformly weighted assessment model could also prove useful in the expert-based experiments that would be needed to elucidate weights and even value functions. We also observed a known shortcoming of SWOT analyses — some metrics can be categorised as several descriptors. Cited SWOT analysis examples addressed this issue and could be used to inform further refinement of S W O and T categorisation. Additionally, while the current SWT and KGs integration with SWOT analysis framework requires human interaction, it could in principle be performed by a dynamic multi-agent system (Zhou et al., 2019).

We anticipate several directions for further work. Deriving diverse metrics requires the integration of additional datasets and urban simulation tools from different domains into the KG. We are also researching how city planning goals and SDGs can be structured ontologically, to develop more robust evaluation approaches.

Acknowledgements

This research is supported by the National Research Foundation, Prime Minister's Office, Singapore under its Campus for Research Excellence and Technological Enterprise (CREATE) programme.

References

Akroyd, J., Harper, Z., Souter, D. N. L., Farazi, F., Bhave, A., Mosbach, S., & Kraft, M. (2021). Universal Digital Twin—Land Use. *c4e-Preprint Series.* Cambridge.

Akroyd, J., Mosbach, S., Bhave, A., & Kraft, M. (2021). Universal Digital Twin—A Dynamic Knowledge Graph. *Data-Centric Engineering*, 2.

Blazegraph. (2020). Geospatial support in Blazegraph. Retrieved November 13, 2021, from https://github.com/blazegraph/database/wiki/GeoSpatial

Chadzynski, A., Krdzavac, N., Farazi, F., Lim, M. Q., Li, S., Grisiute, A., Herthogs, P., et al. (2021). Semantic 3D City Database—An enabler for a dynamic geospatial knowledge graph. *Energy and AI*, 6, 100106.

Chadzynski, A., Li, S., Grisiute, A., Farazi, F., Lindberg, C., Mosbach, S., Herthogs, P., et al. (2021). Semantic 3D City Agents—An intelligent automation for Dynamic Geospatial Knowledge Graphs. *c4e-Preprint Series*. Cambridge.

Comino, E., & Ferretti, V. (2016). Indicators-based spatial SWOT analysis: Supporting the strategic planning and management of complex territorial systems. *Ecological Indicators*, 60, 1104–1117.

Data.gov.sg. (2021). *Dataset List*. Retrieved November 13, 2021, from https://data.gov.sg/search?groups%3Denvironment

Eibeck, A., Chadzynski, A., Lim, M. Q., Aditya, K., Ong, L., Devanand, A., Karmakar, G., et al. (2020). A Parallel World Framework for scenario analysis in knowledge graphs. *Data-Centric Engineering*, 1.

Energy Market Authority. (2017). Renewable Energy—Overview. Retrieved February 4, 2017, from https://www.ema.gov.sg/Renewable_Energy_Overview.aspx

Ervural, B. C., Zaim, S., Demirel, O. F., Aydin, Z., & Delen, D. (2018). An ANP and fuzzy TOPSIS-based SWOT analysis for Turkey's energy planning. *Renewable and Sustainable Energy Reviews*, 82, 1538–1550.

Ghazinoory, S., Abdi, M., & Azadegan-Mehr, M. (2011). SWOT methodology: A state-of-the-art review for the past, a framework for the future. *Journal of Business Economics and Management*, 12(1), 24–48.

Grisiute, A., Silvennoinen, H., Shi, Z., Chadzynski, A., Li, S., Lim, M. Q., Sielker, F., et al. (2021). Creating multi-domain urban planning indicators using a knowledge graph: A district energy use case in Singapore. *Presented at the International Conference on Evolving Cities*, Southampton, UK.

Learned, E. P., Christensen, C., Andrews, R. S., & Guth, D. (1965). *Business policy: Text and cases*. Irwin Publishers.

Massaro, E., Athanassiadis, A., Psyllidis, A., & Binder, C. R. (2020). Ontology-Based Integration of Urban Sustainability Indicators. In C. R. Binder, E. Massaro, & R. Wyss (Eds.), *Sustainability Assessment of Urban Systems* (pp. 332–350). Cambridge University Press.

Richthofen, A., Herthogs, P., Kraft, M., & Cairns, S. (2022). Semantic City Planning Systems (SCPS): A Literature Review. *Journal of Planning Literature*, 08854122211068526.

Shi, Z., Fonseca, J. A., & Schlueter, A. (2017). A review of simulation-based urban form generation and optimization for energy-driven urban design. *Building and Environment*, 121, 119–129.

Shi, Z., Fonseca, J. A., & Schlueter, A. (2021). A parametric method using vernacular urban block typologies for investigating interactions between solar energy use and urban design. *Renewable Energy*, 165, 823–841.

Shi, Z., Herthogs, P., Li, S., Chadzynski, A., Lim, M. Q., Richthofen, A. V., Cairns, S., et al. (2021). Land Use Type Allocation Informed by Urban Energy Performance: A Use Case for a Semantic-Web Approach to Master Planning. *The 26th International Conference of the Association for Computer-Aided Architectural Design Research in Asia, CAADRIA 2021* (Vol. 2, pp. 679–688).

Shi, Z., Hsieh, S., Fonseca, J. A., & Schlueter, A. (2020). Street grids for efficient district cooling systems in high-density cities. *Sustainable Cities and Society*, 60, 102224.

URA. (2021). Urban Transformations. Retrieved November 13, 2021, from https://www.ura.gov.sg/Corporate/Planning/Master-Plan/Urban-Transformations

W3C. (2013). SPARQL Query Language for RDF. Retrieved November 14, 2021, from https://www.w3.org/TR/rdf-sparql-query/

White, T. H., de Melo Barros, Y., Develey, P. F., Llerandi-Román, I. C., Monsegur-Rivera, O. A., & Trujillo-Pinto, A. M. (2015). Improving reintroduction planning and implementation through quantitative SWOT analysis. *Journal for Nature Conservation*, 28, 149–159.

Winkelhake, U. (2018). *The Digital Transformation of the Automotive Industry.* Springer International Publishing.

Zhou, X., Eibeck, A., Lim, M. Q., Krdzavac, N. B., & Kraft, M. (2019). An agent composition framework for the J-Park Simulator—A knowledge graph for the process industry. *Computers & Chemical Engineering*, 130, 106577