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Toward Designing with Heterogeneous Values
— A Graph Data Representation for Constructive
Problem Framing in Multi-Objective Street Design

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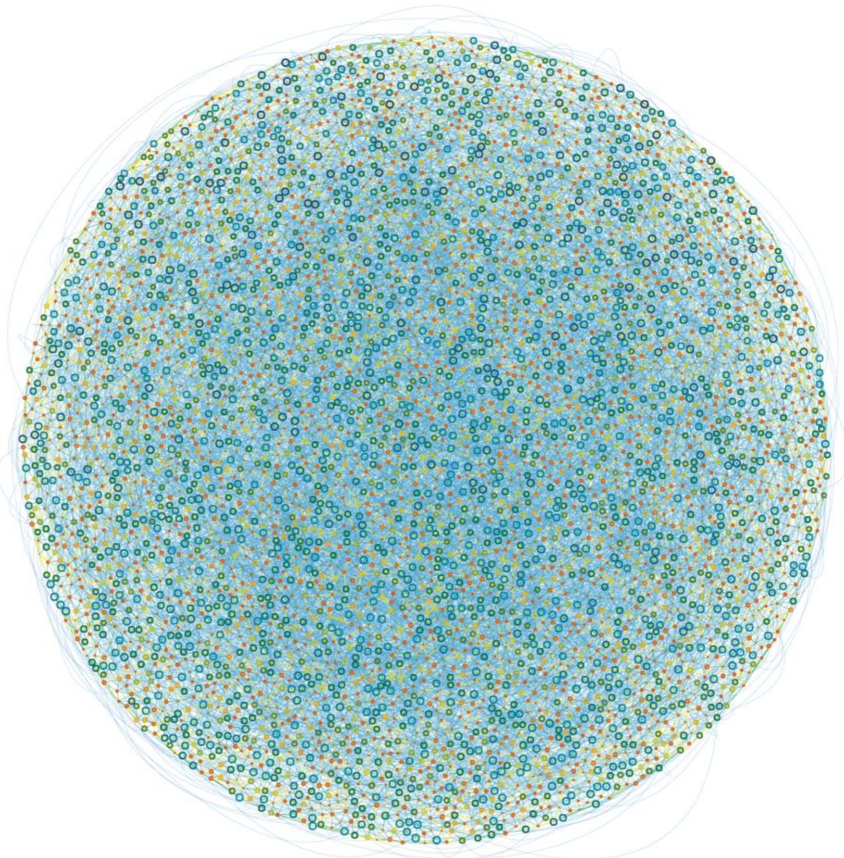

Toward Designing with Heterogeneous Values

— A Graph Data Representation for Constructive Problem Framing in Multi-Objective Street Design

by Jiawei (Vincent) Mai, 2020

Acknowledgement

The research and writing of this thesis had been a tumultuous process. This can be attributed to factors both personal and external. I had developed a strong interest in the diversity of values, particularly its role in conceptual framing in collective design settings. Led by my curiosity and ambition, I had journeyed through fascinating and vast knowledge domains, yet few can be thoroughly studied in the short duration of a master's thesis. In short, I had a hard time scoping down the research until its submission, and this is the personal factor. The external factor is the unannounced arrival of a pandemic amid the thesis semester, bringing tremendous disruption to everyday life, alongside which, much isolation and distress.

It is through such unusual circumstance that I would like to express my gratitude, especially to those supported me through this thesis. To my academic advisor Dr. Daniel Cardoso Llach, who, in the past two years, had offered me numerous opportunities in research, critical feedback for my thesis, and unwavering support during the pandemic. To Director Ray Gastil, who had helped me arrived at a workable research topic and shared with me his decades of expertise and insights in urban planning and design.

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Abstract

The process of urban design can be viewed as complex negotiations among heterogeneous value agendas representing different stakeholders. As a result, any urban design problem can yield a multitude of framings, each delineates a distinct approach to address its underlying objectives. Planners and designers frequently face the unwieldy challenge of the growing complexity of design problems, characterized by a large set of interwoven and often competing objectives.

Shrouded in complex objectives and uncertainty, how can representations of design strategies provide affordance in the framing of urban design problems? Focused on multi-objective street design as the principle subject of investigation, this thesis proposed a representation of design strategies, integrating Object Process Methodology, Dynamic Bayesian Network, and graph data modeling. Subsequent experiments demonstrated that a design strategy represented as system architecture can encode the framing of its value propositions. The incorporation of Bayesian inference can meaningfully compute uncertainties in both the design and its context while supporting evidence-based belief-update. Finally, a graph data model can afford computational analyses that unveil latent interactions between different value framings, synergistic or conflicting, thus informs the reformulation of the design problem.

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1. Introduction

> *"Always design a thing by considering it in its next larger context—a chair in a room, a room in a house, a house in an environment, an environment in a city plan."*
>
> —Eliel Saarinen

A designed artifact or system inevitably interfaces with a broader nexus of agents and systems which, at its boundary, forms its context. Context is what gives design purposes. Designing a chair in silos makes it brittle, unusable, or irrelevant; planning a transit system without rigorously assessing its regional impact brings forth unintended consequences for decades to come. As Eliel Saarinen shrewdly pointed out, design involves understanding the "next larger context" in which a design is situated and that which gives rise to the problem of design.

Saarinen had urged us to look beyond the endogenous concerns of design in search of broader framings. Nevertheless, it remains ambiguous what to look for in a design's "next larger context". For a chair, its context can be its users, support for postures, its manufacturing process, or its relation to the interior in which it sits. On the other hand, how might one start to identify factors salient to a transit network: the choice of vehicle, the efficiency of its operation, the source of funding, the experience of its riders, the streets and neighbor it serves, its proximity to other transit options, its impact on urban growth or infill development, on regional economy and job growth, on traffic congestion, on air quality, or on public spaces? These questions merely offer us a glimpse into its potentially vast and intricate context. As the scale of urban systems enlarges, its next immediate context became increasing nebulous and its problem scope difficult to delineate.

1.1 The Wickedness of Cities

The city as a problem was formally described as "wicked" in *Dilemmas in a General Theory of Planning*. The wickedness that Rittel and Webber faced lies in the problem's ill-defined nature where its goals are contentious and its formulation forbidding.[1] What gave rise to such wickedness is the complex web of causalities innate in the phenomenon of cities. Journalist and author Jane Jacobs, citing scientist Warren Weaver, referred to it as "organized complexity"[2] involving a sizable number of interconnected factors forming an organic whole.[3] Look no further than an urban street, where adjacent facades and canopies of street trees form its enclosure; where street parking and bicycle lanes buffer the edge of sidewalks from road traffic; where a variety of storefronts and outdoor seating provide places to see and be seen; where proximity to public transit affords ease of access and in turn benefits local businesses. All these elements work in concert to foster a safe and vibrant street. While safety and vibrancy might be recognized qualities with enumerable contributing factors, it is less evident wherein lies the connection between reducing intersection delay and the hinderance of infill developments. The enormity and intricacy of a city—the sheer number of actors, factors, and their interdependencies—have made its overall comprehension formidable if not next to impossible. Individuals possessing partial views voice heterogenous propositions of what cities ought to be, while the entangled web of causality beclouds the delineation of any problem boundary. In short, the city as a problem is, indeed, "wicked".

It is easy to reach an impasse in face of a wicked problem as one quickly becomes overwhelmed by its complexity. Some simply relinquish attempts to grasp the issue; still many choose to reduce the problem down to a handful of linear causalities. During the post-war era, the need to alleviate traffic congestions had made way for road widening at the expense of intricate street functions vital to urban life.[4] While the automobile may have been a convenient scapegoat for the ills of orthodox planning, Jacobs astutely pointed out that the real cause lied in planners' substituting the problems of the city with the problem of

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[1] Rittel and Webber, "Dilemmas in a General Theory of Planning."
[2] Weaver, "Science and Complexity."
[3] Jacobs, Death and Life of Great American Cities. p. 432.
[4] Ibid. p. 338-371.

automobiles, or rather, in our poor grasp on the kind of problem a city was.[5] Nearly half a century later, we found ourselves mired in the exact situation as we grapple with the unintended consequences brought about by planning decisions made decades earlier. California's recent shift from Level of Service (LOS) to Vehicle Miles Traveled (VMT) as its traffic impact measure[6] was telling of the ripple effects from the narrow focus on improving motorway efficiency. LOS of an urban intersection is a grade measure based on vehicle delays. Owing to the near-threshold LOS grades for many intersections in dense urban regions, new in-fill developments are likely to trigger a downgrade and in turn bear the responsibility of traffic mitigation.[7] The high cost of mitigation either incentivizes more greenfield developments further away from the city or goes into road widening and other measures which degrades walkability and livability of existing neighborhoods.[8] Less conspicuous impacts include increased runoff and the risk of flooding on more impermeable pavements; worsen accessibility to economic opportunities and other city services from sprawling and separation of uses, while ironically creating more traffic congestions.[9]

Our linear and reductive reasoning had come up short against the multi-objective, complex and uncertain nature of problems of cities. The multi-objectiveness echoes an increasingly diverse set of stakeholders who represent heterogeneous value propositions. Traffic engineers focus on the operational efficiency of transportation, real estate developers concern with the cost and return of investment, neighborhood residents advocate for walkability and social interactions. Despite our best effort in taming the problem, a distilled set of objectives is inevitably tethered to broader agendas. Illustrated in the above example, strategies alleviating traffic delays ended up undermining efforts in creating walkable neighborhoods, mitigating stormwater runoff, and improving access to jobs and services. Thus, it is not only the number of objectives but their complex coupling that make many urban issues thorny. Mitigating LOS impact at an intersection had inadvertently galvanized sprawling developments, thereby increasing dependence on driving and paradoxically exacerbating traffic congestions. These complex coupling, as Rittel and Webber had pointed out, convolute the source of the problem, making it unclear where and how to intervene even

[5] Ibid. p. 7.
[6] "Transportation Impacts (SB 743) - Office of Planning and Research."
[7] Ibid.
[8] Ibid.
[9] Ibid.

when our objectives are explicit.[10] Such inherent complexity begets a great deal of endogenous uncertainties in existing urban issues, as it remained difficult to predict wider repercussions of local interventions. Worst still are the exogenous uncertainties introduced by an evolving society. Adoptions of new technologies such as ridesharing, regulatory shifts replacing LOS with VMT, or a changing climate that precipitates more severe flooding, all further confound existing urban issues with more contingent factors and interdependencies.

In face of the wickedness of urban issues, what sensible approaches might aid planners, designers and other stakeholders in their decision making? The following presents, in the context of planning, an overview of two schools of thought—systems thinking and design thinking. The former devises methodologies in coping with large numbers of interacting variables and the latter offers tried approaches in dealing with ill-defined problems.

1.2 Systems Thinking

Our understanding of the problems of cities, particularly our ability to describe their complexities, is intimately tied to the study of systems. Rittel and Webber viewed the intractability of goal definition and problem formulation through analyzing open and interconnected systems of social processes. Similarly, Jacobs spoke of the phenomenon of cities as an organic whole emerged from complex interactions across sizable numbers of factors. Perspectives as such are underpinned by conspicuous systems thinking—a paradigm of seeing objects and phenomena as a set of interrelated entities, with the aim of understanding their emergent functionalities and properties.

Distinguished by its ability to deal with large number of interacting variables and their relations,[11] systems approach to planning started gathering momentum in late 1960s, notably with the publication of *Urban and Regional Planning: A Systems Approach* by McLoughlin[12]. Urban researchers Batty and Marshall discussed the criticism which early

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[10] Rittel and Webber, “Dilemmas in a General Theory of Planning.” p. 159.
[11] “Systems Approaches to Urban Planning: Mixed, Conditional, Adaptive and Other Alternatives: Institute of Physical Planning, Research Report No. 6 (August 1970).”p. 399.
[12] McLoughlin, Urban and Regional Planning.

systems approach had garnered—in particular, the view of cities as control systems (Cybernetics) and its continuation of the lineage of top-down orthodox planning.[13] Indeed, the belief that planning and design are means to steer cities toward a preconceived equilibrium—much like a thermostat regulating temperature to a preset level—differs little from imposing an idealized model of the city. On the other hand, Rittel and Webber criticized early systems approaches in their fallacy of—"first understand then solve"—phase-based planning.[14] While a simple control system must have a clear goal of maintaining homeostasis, the complexity and uncertainty of cities defy simple goal specifications, thereby rendering an homeostasis (an ideal vision of cities) moot.

As early systems approach continued to encounter setbacks in practice, alternative modeling techniques, as exemplified in *Urban Dynamics* by Jay Forrester[15], began to address the complexity that made problems of cities "wicked". Batty gave a detail account of the development in land-use and transportation models in the past five decades, drawing parallels between modeling approaches, urban developments, and planning paradigms.[16] Without excessive elaboration, it is worth noting a conceivable shift from the early macro, static modeling approaches based on regional science and urban economic theory in 1960s, to the micro, dynamic approaches such as Cellular Automata and Agent-based Modeling charactering 1990s and onward.[17] Paralleled this change was a paradigmatic shift in planning practices from top-down, centralized approaches serving idealized yet static cities to ones that are bottom-up and participatory, reflecting a city's innate heterogeneity and uncertainty.[18] As successive modeling approaches revealed an ever growing schism between simplified systems and their messy, real-world counterpart, the aim of modeling had gradually migrated from future prediction and operational management to ones that facilitated understanding and informed speculations.[19]

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[13] Batty and Marshall, "The Origins of Complexity Theory in Cities and Planning." in *Complexity Theories of Cities Have Come of Age*, eds. Portugali et al. p. 26-33.
[14] Rittel and Webber, "Dilemmas in a General Theory of Planning." p. 162.
[15] Forrester, Urban Dynamics.
[16] Batty. "Fifty Years of Urban Modeling: Macro-Statics to Micro-Dynamics." in *The Dynamics of Complex Urban Systems: An Interdisciplinary Approach*, eds. Albeverio.
[17] Ibid.
[18] Ibid.
[19] Ibid. p.11, 17.

Although early systems approaches had grossly simplified cities, systems thinking alongside the rise of complexity theory remained relevant and useful means for studying cities. The hope that we can understand *then* plan cities, though, had hitherto been proven an impractical delusion. Without an exhaustive comprehension of cities, perhaps a sensible alternative (indeed what is done in practice) is to act on our partial understandings, yet to remain open-minded such that both our understanding and solution can evolve over time. Iterative approaches as such are, in fact, commonly devised in a wide range of design practices. In the following section we thusly turn to design thinking where iterations of problem framing and problem solving are done in concert, where divergent thinking and the inclusion of heterogeneous viewpoints aid designers' navigation through open-ended problems.

1.2 Design Thinking

If systems thinking had lent us a framework that illuminates the complexity of urban issues, then design thinking had offered us a generalized process and a wealth of tried approaches in tackling ill-defined problems. Nigel Cross had identified 1960s as the period of 'design methods movement' where processes of design were studied and examined with objectivity and rationality, culminating in the publication of *Science of The Artificial* by Herbert Simon.[20] This had laid the foundation for design thinking, where the generalized concern of designing can be decoupled from specific design disciplines.[21]

Design is fundamentally driven by intentionality. To design, as Simon had put, is "to devise courses of action aimed at changing existing situations into preferred ones."[22] However, as discussed earlier, it is precisely the defining of intents that highlights the challenges of planning. In critiquing "Technical Rationality", Donald Schön pointed out that "design science" as proposed by Simon only applied to "well-formed problems" where the desired conditions were known and the search of solutions may ensue.[23] At the heart of Schön's

[20] Cross, Designerly Ways of Knowing. p. 95-103.
[21] Ryan, "A Framework for Systemic Design." p. 2
[22] Simon, The Sciences of the Artificial. p. 55·
[23] Schön, The Reflective Practitioner. p. 39-49

critique lies Technical Rationality's skewed emphasis on problem solving using well-formulated techniques whereas the messy reality of practice often presents no readily solvable problems. Instead, they must be "constructed" from a problematic context.[24] By "constructed", Schön meant the selection of a set of "things" that constitutes a situation and the deliberation or "framing" of why they are problematic.[25] For instance, a planner might attribute perils of a street to unsafe vehicle speed and interpret the problem as design speed limit; or to hone in on the conflicts between various uses such as street parking, cyclists and bus boarding, thereby determining the issue as the designation of uses. Building on Schön's argument, Kees Dorst had also argued that design problems occurred when they go beyond the bounds of prescribed approaches; thus, a new approach or "frame" must be created for both problem and solution formulations.[26]

Design thinking's emphasis on "problem setting", however, does not imply a sequential "define-then-solve" approach, rather scholars had identified that problem definition and solution as occurred iteratively and in tandem. Schön proposed "reflection-in-action"—where practitioners reflect in (or on) their practice to explore and experiment on new framings—as a key process in dealing with ill-defined problems.[27] Thus, practitioners no longer passively apply or impose established approaches; rather, the "means" are ingrained in the inquiry of desired "ends", and "doing" incorporated into "thinking".[28] Similarly, Dorst and Cross had observed that designers devised solutions as conjectures in their exploration and formulation of design problems.[29] In planning, Rittel and Webber had likewise argued that the information needed to describe the problem was dependent on the solution conjectures.[30] For instance, in order to improve street safety, urban designers may have initially devised speed tables as an interim strategy for reducing vehicle speed. Nevertheless, the annoyance induced on driving may lead drivers to alternative routes altogether and inadvertently diverts traffic from existing retail and businesses—a latent dimension yet to be accounted for in the problem formulation. Thus, it is with such approach that design thinking

[24] Ibid. p. 39-43.
[25] Ibid. p. 40.
[26] Dorst, Frame Innovation. p. 49-55.
[27] Schön, The Reflective Practitioner. p. 49-69.
[28] Ibid. p. 68, 69.
[29] Dorst and Cross, "Creativity in the Design Process."
[30] Rittel and Webber, "Dilemmas in a General Theory of Planning." p. 161.

prompts critical reflections and guide practitioners' actions in coping with ill-defined problems.

The reflective nature of design thinking, in the context of urban planning and design, had assumed a collective dimension in coping with the heterogeneity in stakeholders' value propositions and domain expertise. More pertinent than ever is the need to facilitate communication amongst stakeholders and to construct share understanding of urban issues. In face of multi-objective, complex and uncertain urban problems, can the representation of design problems and solutions—the very medium for exchanging thoughts—facilitate collective reflection and aid stakeholders in both problem understanding and problem solving?

2. Modeling and Decision Support in Planning

This chapter examines several important approaches in the modeling of urban problems and their role in decision support in design and planning since 1960s. With no intention of conducting a comprehensive review, the author studied how each method had addressed aspects characterizing problems of cities, namely, multi-objectiveness, complexity, and uncertainty. In analyzing existing methods, the author attempts to answer the following two questions:

> 1) How did the method represent the problem of and/or solutions to an urban issue?
> 2) How might such representation facilitate collective reflection amongst stakeholder?

2.1 Design Knowledge Representation

In his PhD dissertation—*Notes on the Synthesis of Form*—Christopher Alexander viewed good design as the "fitness" between the form in question (the design solution) and its context (the design problem).[31] In the absence of a unitary context description, a design problem can be more effectively distilled into a finite set of requirements based on recognizable "misfits".[32] For instance, in designing a public square, instead of conjuring up an inexhaustible list of the desired qualities, one can inversely generate the requirements from observable undesired qualities (misfit variables) such as the lack of shading, the occlusion of visual prospect, or the disconnect from public transit.

Naturally, the goal of form-making is to rectify all misfits. Nevertheless, Alexander had observed that the complexity of contemporary design problems, namely the number of requirements and their intricate coupling, had far exceeded the intuitive grasp of an individual designer.[33] In view of such challenge, Alexander had devised an analytical process where

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[31] Alexander, Notes on the Synthesis of Form. p.15
[32] Ibid. p. 26
[33] Ibid. p. 5

the problem was represented as a graph G = {M, L} that denoted a set of misfits (M) and their interactions (L), which could then be algorithmically decomposed—by identifying clusters in the graph—into a tree-like hierarchy of requirements. Disentangled, the hierarchy of requirements, seen as a bona fide "program" for the design, could be addressed relatively independently in the synthesis of design solution. The result of Alexander's approach was a set of "constructive diagrams" which simultaneously encapsulated key qualities in both requirements and forms.[34]

In the worked example of a design for an agricultural village in rural India, Alexander had demonstrated that the analytical process of requirement decomposition could reveal the latent structure of the design problem, which had formed the basis for the synthesis of "well-fit" forms. Thus, the proposed method served the dual purposes of aiding designers' understanding of the design problem by disentangling its complexity and consequently affording clarity and ease in their solution creation. In contrast with the iterative co-evolution of problem definitions and solution as discussed in the introduction, Alexander had shown a far more linear— "understand-then-solve"—approach. This can be attributed to the Alexander's algorithm which was designed to yield the best decomposition so that the derived hierarchical requirements are the least entangled. Yet such optimality may be dubious. Pointed out by Alise Upitis, Alexander's basis for identifying interactions between design requirements wad done at the discretion of the designer and varied largely, as he alternated from "almost logically necessary" to "almost by definition" to "on physical laws".[35] Alexander had offered no clue in discerning interactions between requirements, especially when they were proposed by stakeholders from disparate domains. Lastly, the merit of the tree-like requirement decomposition was called into question by Alexander himself as he later discussed in *A City is Not A Tree*. A hierarchy of independent requirement, after all, may not be appropriate for describing cities whose richness lies precisely in the overlaps of different functions.[36]

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[34] Ibid. p. 84-94
[35] Upitis, "Alexander's Choice." in *A Second Modernism,* eds. Dutta.
[36] Alexander, "A CITY IS NOT A TREE."

2.2 Modeling and Simulation

2.2.1 System Dynamics

Systems Dynamics (SD) is a system modeling methodology developed by Jay W. Forrester in 1950s as an attempt to understand non-linear behaviors of complex feedback systems, particularly in business and other social systems.[37] Published in 1969, *Urban Dynamics* marks the earliest application of SD in policy issues.[38] Drawn from the field of Cybernetics[39], SD is interested in modeling causal feedback loops between key variables in the system under study. These casual relationships are typically represented by differential equations, while the dynamic of the system, i.e., the integrals of these functions over time, can be numerically simulated in discrete timesteps.

In *Urban Dynamics*, Forrester had set out to model the implication of the increase in low-cost housing stocks—one of the government's programs in 1960s—when American cities are mired in economic distress, as reflected in widespread unemployment and housing deterioration.[40] Key indicators representing the depressed urban areas include employment rates and housing affordability. Other key systems variables include population density, job opportunities, business occupations, and aging of buildings. The effect of increasing low-cost housing stock had been conceived with such certainty to a degree that defied even the need for modeling. Nevertheless, results yielded from the simulation had demonstrated a scenario far counterintuitive and controversial. A vicious cycle was formed when excess low-cost housing stocks had ended up attracting low-income population beyond job supply while the developments took over valuable land which could have been occupied by new businesses.[41]

SD had offered planners a way of experimenting with the uncertainty and complexity arise from non-linear, causal feedbacks endogenous to the underlying structure of many urban issues. Given a set of variables configured to represent the initial condition of a city, SD can

[37] Forrester, Industrial Dynamics.
[38] Forrester, Urban Dynamics.
[39] Wiener, Cybernetics or Control and Communication in the Animal and the Machine.
[40] Forrester, "Counterintuitive Behavior of Social Systems."
[41] Ibid

simulate the impact of a policy proposal over time. In theory, SD could allow stakeholders to elicit "backtalk" from the problem modeled and whereby facilitate better understanding of both the urban issues and the policies proposed. Nonetheless, despite its applicability in public policies, SD had yet to witness wide adoptions amongst policy makers, thus it is worth noting several limitations arise from such an approach. The most prominent one is the difficulty in circumscribing an urban issue. SD relied on the assumption that all relevant causes and effects exist only within the system; yet it was precisely the evasive boundary that marked an urban problem wicked. More broadly, Forrester pointed out that the resistance to SD was largely a consequence of the modeler's inability to bridge the gap between stakeholders' mental models and the complexity of the simulated system.[42] In more recent studies, Ghaffarzadegan, et al. had argued that smaller (or simpler) SD models had been proven to be more effective in public policy process, yet the pursue of parsimony can potentially impede the rigor in the modeling of policy issue, i.e., when model simplicity takes precedence over ensuring the presence of all key factors and the clarity of their relationships.[43]

2.2.2 Agent-based Modeling

In contrast to the aggregate approach of System Dynamics, Agent-based Modeling (ABM) utilizes a disaggregate approach to represent the system under study. As discussed in "systems thinking" in the introduction, it reflects the paradigm shift from a centralized to a bottom-up approach in planning in recognition of the complexities of cities. It is worth mentioning a closely related modeling method—Cellular Automata (CA). Invented by Stanislaw Ulam and Jon Von Neuman in 1940s, CA can be understood as a grid of cells, each characterized by one of its finite states and the transition of cells as a function of the states of their surrounding neighbors. Batty was amongst the earliest adopters to apply CA in urban studies thanks to its added spatial dimension and better resemblance of the actual development of city plots.[44] Productive as it had been in exploring the complexity and

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[42] Forrester, "Systems Dynamics and the Lesson for 35 years." in *A Systems-Based Approach to Policymaking*, eds. De Greene. p. 219-220
[43] Ghaffarzadegan, Lyneis, and Richardson, "How Small System Dynamics Models Can Help the Public Policy Process."
[44] Batty, "Cellular Automata and Urban Form."

emergence in urban systems, CA was nevertheless hindered by its relative simplicity such as fixed cell locations, static neighbors, and limitation of its transition rules.[45] If the cells in CA can be viewed as a special case of an "agent", then ABM can be understood as a generalized CA. In ABM, agents can autonomously interact with other agents while their state transitions no longer determined by simple rules but more sophisticated belief models of their 'environment'.[46]

A classic example of ABM is Schelling's Model of Segregation[47] in which two groups of agents occupies an N by N grid (where the number of agent $< N^2$), each characterized by a "tolerance threshold", i.e., the minimum percentage of its surrounding neighbors from the same group. In each time-step, an agent chooses to relocate to an empty cell when the number of neighboring agents (from the opposite group) exceeds its tolerance threshold. Thus, the system was entirely driven by the behavior of individual agent with the goal of studying the resulting patterns at a macro scale. Even though the tolerance threshold was set at 1/3, that is, the agent was mildly intolerant of being surrounded by the outgroup, a clear segregation pattern had nonetheless emerged, defying expectation. Simple as it is, Schelling's Model of Segregation had nevertheless demonstrated the complexity risen from many interacting agents and its environment, thus demonstrating the potential in the study of urban dynamics.

In more recent studies, Batty had demonstrated the flexibility of ABM in modeling geo-spatial systems at varying scales, ranging from pedestrian movement patterns in buildings and streets to the urban sprawl of cities.[48] The work of Batty and colleagues had demonstrated that agents governed by simple behavioral rules can indeed generate macro patterns recognizable in the real-world, yet a new set of limitations ensued. Contrary to System Dynamics, which explicitly, albeit coarsely, models policy interventions within a system, it is can be rather difficult to model how policies affect individual agents. The representation of policy and design intervention begs the question of the level of abstraction at which an agent should be modeled. For instance, to model pedestrians as agents, their behavioral model

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[45] Santé et al., "Cellular Automata Models for the Simulation of Real-World Urban Processes.".
[46] Crooks and Hepenstall. "Introduction to Agent-Based Modelling." In *Agent-Based Models of Geographical Systems*, eds. Heppenstall et al.
[47] Schelling, "Dynamic Models of Segregation†."
[48] Batty, "Agents, Cells, and Cities."

governing physical interactions with traffic and street elements differ substantially from those governing their choice of transportation and other urban services. Crooks and Heppenstall had elaborated the challenge of balancing realism and simplicity: too simple of an abstraction fails to capture key behavior variables; too complex of an abstraction renders the model difficult to understand, calibrate, and validate.[49] Other factors such as sensitivity to initial conditions also significantly curb the predictiveness of ABM-based urban models in policy applications.[50]

[49] Crooks and Hepenstall." Introduction to Agent-Based Modelling." in *Agent-Based Models Of Geographical Systems*, eds. Hepenstall et al. p. 98-99
[50] Ibid.

3. Methodology

3.1 Research Questions and Approach

The motivation underlying the research is that value propositions driving urban design and planning strategies are intricately interconnected across time and spatial scales. In light of California's shift in its transportation metrics from Level of Service (LOS) to Vehicle Miles Traveled (VMT), recent studies had revealed latent trade-offs between mitigation of LOS impact, the incentivization of in-fill development, and the reduction of greenhouse gas emissions.[51] Value trade-offs as such, when left unexamined and unleveraged, had led to planning and design decisions siloed in automotive mobility with little consideration on their long-term and regional impact on economic development and environmental qualities.

To obtain insight into the complex interactions amongst a wide range of heterogeneous values, a natural inclination is to conduct more comprehensive urban analyses in hopes of yielding more pertinent problem-framing. Yet strategies as such are inherently resource-intensive, demanding extensive studies of value metrics obtained from various domains early in the planning process. Moreover, it may be difficult to foresee nuanced interactions between disparate value propositions without first visualizing how they can be delivered in concrete design strategies. Enmeshed in the complexity and uncertainty at the scale of a city, the salience of certain trade-offs might not be immediately apparent as their effect only unfold in the long run.

Acknowledging the infeasibility of a top-down and exhaustive approach in studying the complex trade-offs amongst heterogeneous values, the thesis instead explores how design strategies framed by finite value propositions can be mobilized such that they can be leveraged to yield insights into the mutual interactions amongst those values, whereby prompting a more complex and salient reframing (Figure 3.1). Thus, within the confines of the research, the author formulates the following research question:

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[51] Volker, Lee, and Fitch, "Streamlining the Development Approval Process in a Post–Level of Service Los Angeles." p. 16.

How can representations of design strategies provide affordance in framing when design problems are multi-objective, ill-defined and uncertain?

To address the research question, the author focused on multi-objective street designs as a principle subject of investigation. Specifically, the author looked at street design guides[52] published by the National Association of City Transportation Officials (NACTO) and carefully examine of how values and objective metrics were used in framing design problems and in guiding developments of integrated design strategies. Subsequently, the author proposed a representation of street design strategies using a system modeling method—Object Process Methodology (OPM) while incorporating Bayesian probabilistic inference to evaluate the uncertainty of the design intervention. Finally, the representation is to be stored in a graph database with an application that analyzes latent interactions among the value propositions encoded in various design strategies.

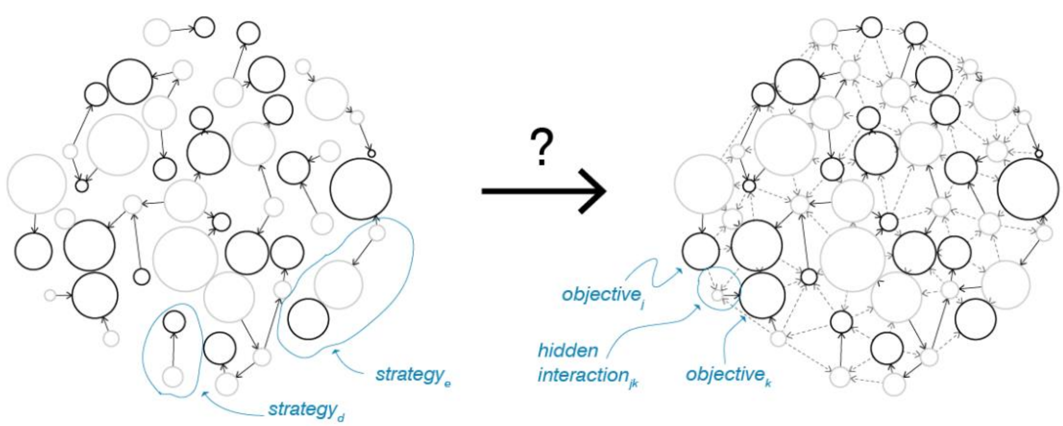

Figure 3.1a
Research Approach: Unveiling Complex Value Interactions from Finite Design Strategies

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[52] National Association of City Transportation Officials, Urban Street Design Guide.

3.2 Urban Street Design

Streets are the most ubiquitous element in the fabric of cities. Streets make up more than 80% of all public spaces, occupying anywhere between a third to a half of all urban land area[53] in many North American cities.[54] As a result, many essential city functions have inevitably been assigned to the domain of streets, such as transportation, water and power infrastructures, green infrastructure, and public spaces. As Jane Jacobs shrewdly summarized in her writing, "streets and their sidewalks, the main public spaces of the city, are its most vital organs."[55] An urban street is legally defined as a public right-of-way, comprised of roadways and sidewalks, flanked by the property lines on either side which define building edges, land uses or setbacks.[56] Within the right-of-way, the roadway is subdivided into different lane spaces, while the sidewalk is composed of various functional zones.

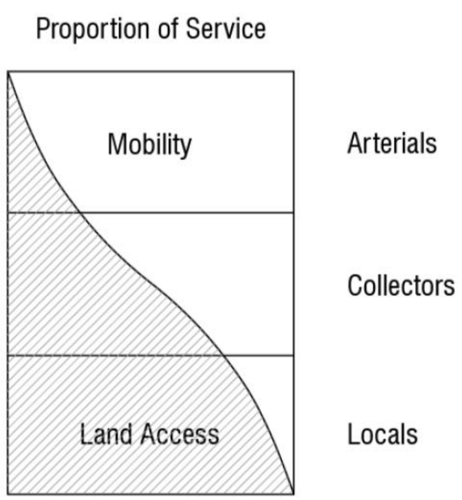

Figure 3.2a
A Policy on Geometric Design of Highways and Streets.
Source: (redrawn from)AASHTO. 2011. AASHTO Green Book.

Figure 3.2b
NACTO Street Design Principles Shows an Integrated, Multi-dimensional Functional Demands for Urban Streets

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[53] Mehta, The Street.
[54] National Association of City Transportation Officials, Urban Street Design Guide.
[55] Jacobs, Death and Life of Great American Cities. p. 50.
[56] Global Street Design Guide. p. 4.

Promoted by the American Association of State Highway and Transportation Officials (AASHTO)[57], street designs in the 20th century was dominated by a dual trade-off between “mobility” and “land access” (Figure 3.2a). This had led traffic engineers to prioritize mobility and optimize for road capacity, which had resulted in streets with over-engineered widths and unsafe speed. In the past two decades, cities across North America had met with the demand for growth due to an influx of population who vied for economic opportunities, increased personal mobilities and access to urban amenities. Coupled with urban growth are more severe and uncertain weather patterns, exacerbated by climate change. These changing demands had incentivized a reframing of urban streets as vital, sustainable, and resilient public spaces that accommodate an expanding set of stakeholders and their needs.

The National Association of City Transportation Officials (NACTO) is an association of 84 major North American Cities and transit agencies, leading the effort in transit-oriented growth by building safe, sustainable, accessible, and equitable transportations.[58] To disseminate its vision, NACTO have published a number of street design guides. Figure 3.2b shows a set of design principles which had been aggregated from Urban Street Design Guide, Global Street Design Guide, Transit Street Design Guide, and Urban Street Stormwater Guide. A sharp contrast to ASSHTO’s dual tradeoffs, NACTO’s design principle shows a far richer framing composed of a set of heterogeneous yet close-knit values.

3.3 Constructive Problem Framing

From vehicle-centric mobility to an integrated vision combining multimodal mobility, ecosystem services and vibrant public spaces, the shift in urban street principles had reflected a substantial reframing of the functionality streets. Not limited to street design is problem framing—a crucial step practiced in almost all design disciplines. In *The Reflective Practitioner*, Schön discussed “problem framing” as following:

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[57] Policy on Geometric Design of Highways and Streets with 2012 and 2013 Errata.
[58] “About NACTO | National Association of City Transportation Officials.”

> *"In order to formulate a design problem to be solved, the designer must frame a problematic design situation: set its boundaries, select particular things and relations for attention and impose on the situation a coherence that guides subsequent moves".*[59]

This view seems to coincide well with the author's training in architectural design: framing involves first distilling a key set of entities and relationships from a nebulous design context, and subsequently devising a "concept" (or "framing") that constrains the solution space.

In *Frame Innovation*, Dorst further developed Schön's view on framing and defined it in terms of "design abduction" reasoning.[60] Without expanding on Dorst's work on design cognition, "design abduction" reasoning can be viewed as a creative exploration on both the "what" and the "how" that may lead to a desired outcome (Figure 3.3a).[61] To put succinctly, Dorst defined framing as a "proposed hypothetical pattern of relationships" that achieves the desired outcome.[62] For instance, the treatment of urban stormwater runoff (the outcome) can be framed as waste to be dispensed quickly via existing gray water infrastructure; alternatively it can also be framed as a constituent of the natural hydrological cycle where it is retained, filtered, or infiltrated slowly before discharging into nearby water body or to replenish groundwater. Here, the two frames correspond to *waste to be dispensed quickly* and *ecosystem services to be performed*, each lead to a different treatment of stormwater runoff. In other words, framing is simply a prescribed approach to problem understanding that which structures our search of the design solution.

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[59] Schön, "Designing: Rules, Types and Worlds." p. 182
[60] Dorst, Frame Innovation. Chapter 3.
[61] Ibid.
[62] Ibid. p.53

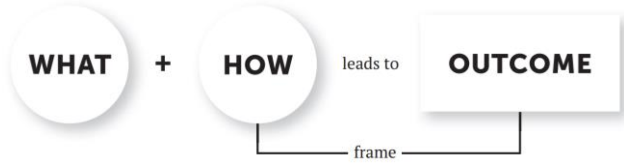

Figure 3.3a
Framing in Design Abduction Reasoning
Source: Dorst, Frame Innovation. p.53

Discussed briefly in the introduction, Dorst and Cross further illuminated on the "co-evolution" of problem framing and problem solving in their protocol studies of expert industrial designers. Put simply, the search of solution does not follow a fixed problem formulation sequentially; rather designers iterate between problem formulation and design solution, developing and refining both until a "matching problem-solution pair"—a "good fit" in Alexander's term—is generated. Cross had also pointed out that designers are "solution-focused" in that they formulate "solution-led" conjectures as means to navigate through both the problem and solution spaces.[63] What Dorst and Cross had theorized is akin to *designing by prototyping* such as using an interim approach of painting a curb extension and evaluating its impact on the behavior of vehicles and pedestrians.

Prior research in design theory had provided a conceptual foundation for what the author referred to as "constructive problem framing". Here, "constructive" simply characterizes "framing" as a plastic and intentional process led by stakeholders in a multi-objective design. Forfeiting a top-down and comprehensive framing of urban design, the thesis was motivated, instead, by the hypothesis that collective framing can be aided by the analysis of latent interactions between various simpler design frames. The inquiry of the thesis thus focused on devising a structural representation of design strategies, each encodes its pertinent value/objective frame. Analyzable by the proposed database application, the thesis explored how design representations can unveil salient interactions amongst different values/objectives, synergistic or conflicting, which serve to inform subsequent (re)framing.

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[63] Nigel Cross, *Designerly Ways of Knowing* (London: Springer, 2006). Chapter 6.

4. Design Strategy Computation Prototype

4.1 Design Overview

The following section introduces a design computation prototype as the vehicle for inquiring how the representation of street design might allow for analysis that unveils latent interactions between different values/objectives. The proposed prototype is a three-tier-graph database where the thesis focuses on the application tier which performs analysis of the street design representations (see figure 4.1a). A three-tier architecture is typically organized as, from the bottom-up, a Data Tier, an Application Tier, and a User Tier.[64] At the lowest level, the Data Tier stores the data, constraints, and a query language for the read-write operation. The Data Tier utilizes *Neo4j,*[65] a popular off-the-shelve graph database, as its implementation. Sitting in the middle, the Application Tier encodes the application logic and serve as an abstraction separating the User Tier and the Data Tier. The top layer is the User Tier where users can visualize, interact, and perform query on the data based on the logic written in the Application Tier. In the interest of resource constrain, the User Tier is left unimplemented, for each implementation needs to be tailored to the expertise and workflow appropriate to specific stakeholders in the street design and planning process.

[64] Ibid.

[65] "Neo4j Graph Platform – The Leader in Graph Databases," accessed April 22, 2020, https://neo4j.com/.

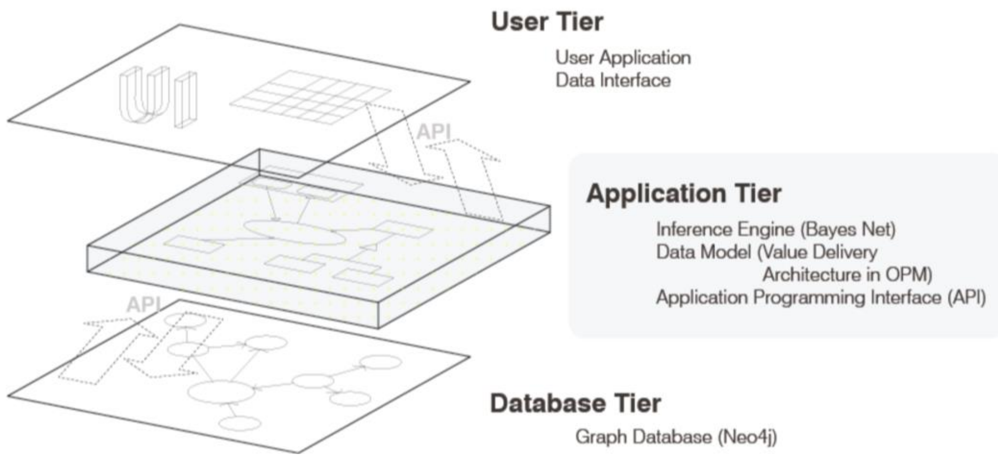

Figure 4.1a
The Architecture of the Proposed Design Database

At the heart of the prototype lies the design of the Application Tier, illustrated as the middle layer in Figure 4.1a. The Application Tier consists of three components. The first component is a data abstraction, atop the Neo4j property graph model, that encodes street design strategies using a system modeling language—OPM. The second component is designed for Bayesian probabilistic inference on the design representations. The third component is the Application Programming Interface (API) which handles communication across all three tiers. The next section elaborates on each of the main building blocks for the Application Tier.

4.2 Application Building Blocks

4.2.1 Design Representation with OPM

Object Process Methodology (OPM) is a popular systems modeling language published in the international standard ISO/PAS 19450[66]. Developed by Professor Dov Dori at Technion at the Israel Institute of Technology, OPM is a general-purpose conceptual and systems modeling method designed to be used by the general public with no presumed background

[66] "ISO/PAS 19450:2015 - Automation systems and integration -- Object-Process Methodology".

knowledge.[67] Although the ontology of OPM is relatively lean (shown in Figure 4.2.1a), it supports modeling of a wide variety of systems, both natural and engineered.

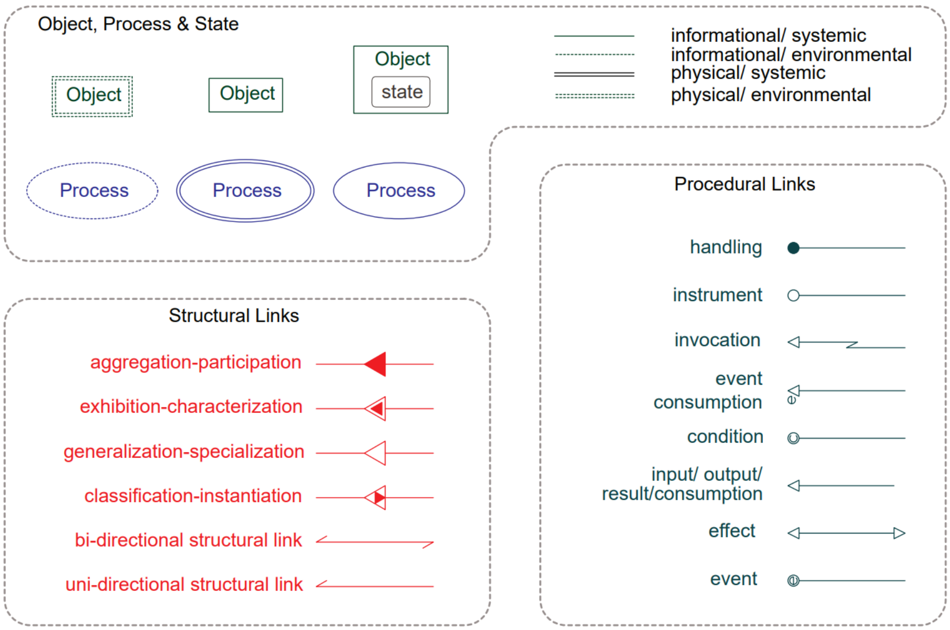

Figure 4.2.1a
Object Process Methodology (OPM) Ontology

The building blocks of OPM is composed of an entity set and a relationship set. The entity set consists of three entities: objects, process, and states. Objects denote a thing that has a stable existence, e.g., a *Person*. States characterizes the status of an object, e.g., *Height* and *Location* (of the *Person*). Processes denote changes or transformations that modify the state of an object, e.g., *Driving* changes the *Location* of the *Person*. To delineate the boundary of a system, OPM differentiates whether an object, a state or a process is *systemic*, i.e. internal to the system, or *environmental*, i.e. external to the system. For instance, a *Person* is external to system of a *Vending Machine*. OPM also characterize whether objects and processes are *physical* or *informational*. For instance, *Vehicles* and *Driving* are *physical* whereas *Speed Limit* and *Planning* are *informational*.

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[67] Dori, Object-Process Methodology.

The relationship set articulates links between objects, processes, and states. A link can be either *structural* or *procedural*. *Structural links* describe the hierarchical relationships between objects, or among processes. For instance, an object *Kettle* is an *aggregation (structural link)* of a *Handle*, a *Body*, and a *Lid*; an object *Student of Design* is a *specialization (structural link)* of the generic *Student*. *Procedural links* denotes functions and are typically used between objects and processes. For instance, an object *Driver handles (procedural link)* the process of *Driving*; an object *Gasoline* is *consumed by (procedural link)* the process of *Combusting*.

The following demonstrates an application of OPM in modeling *Lane Narrowing* as a street design strategy. Figure 4.2.1b shows a mapping from the value *Safety* (left of the dashed box) to the design implementation (dashed box) as well as its context (right of the dashed box). Suppose the Department of Transportation (DoT) of a city values the safety of streets and had assigned a traffic engineer is to improve it. She ended up selecting *Vehicle Speed (object)* as a metric, which is a *specialization (structural link)* of the value *Safety*, and her preliminary approach is *Slowing (process)* it down. The design solution which *enables (procedural link)* such process is a narrower *Lane Width (object)* which requires the act of *Reducing (process)* to *change (procedural link)* its current width from *13 feet (state)* to *10 feet (state)*. Finally, *Reducing (process)* is *handled (procedural link)* by the *DoT (object)*.

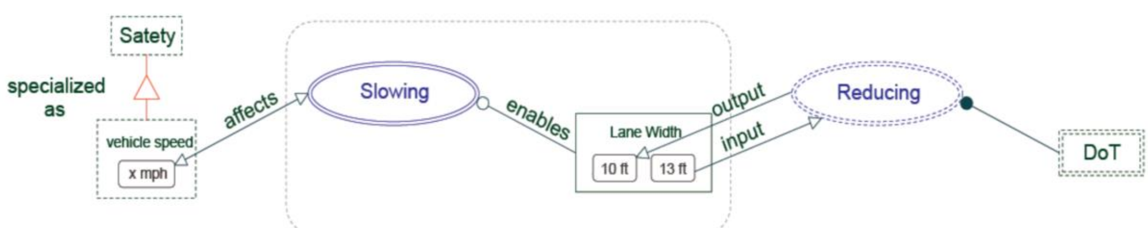

Figure 4.2.1b
Lane Narrowing Strategy as an OPM Diagram

Now that we have modeled a specific design strategy, let us explore a generalized representation that can be applied to a wide variety of strategies. Figure 4.2.1c. shows an elaborated architecture of a generic Value Delivery Strategy (VDS). In the left-dashed box, we see the *Value* representing a desired outcome. Beneath it is the *Metric*, a proxy of the *Value* whose measurement we wish to change. In the middle-dashed box, the system is described in terms of its primary function or *Systemic Process* which *changes* the *Metric*, and the "Form" which *enables* the *Systemic Process*. Finally, to the right is the context which provides the necessary conditions for the systems to exist. The generic VDS can serve as a template for future modeling of any street design strategy.

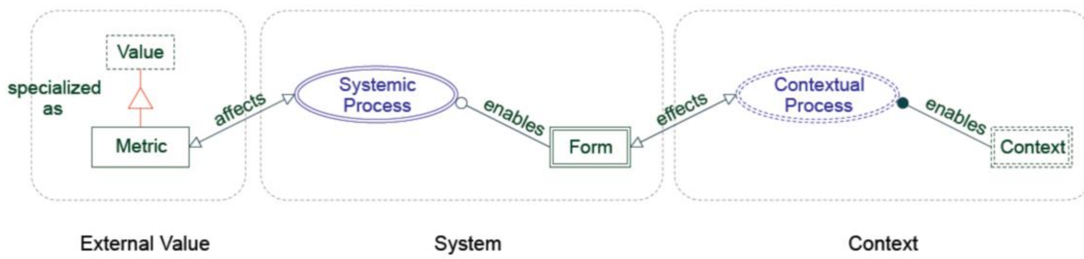

Figure 4.2.1c
Generalized Template for Value-Delivery Strategy (VDS)

Thus far we had only demonstrated the representation of a simple *Lane Narrowing* strategy which can seem contrived. Nevertheless, OPM is designed to describe systems with an arbitrary level of abstraction. It is the modeler's decision to determine the level of detail pertinent to a design strategy. To manage complexity of the system, OPM provides several built-in methods, including: *folding/unfolding*, for abstracting or specifying details in a model; *in-zooming or out-zooming* for showing or hiding subprocesses and intermediate objects; and *state expressing and suppressing* which expresses or suppresses the number of states an object can take. Figure 4.2.1d illustrates a more granular view of the generic VDS shown in Figure 4.2.1c.

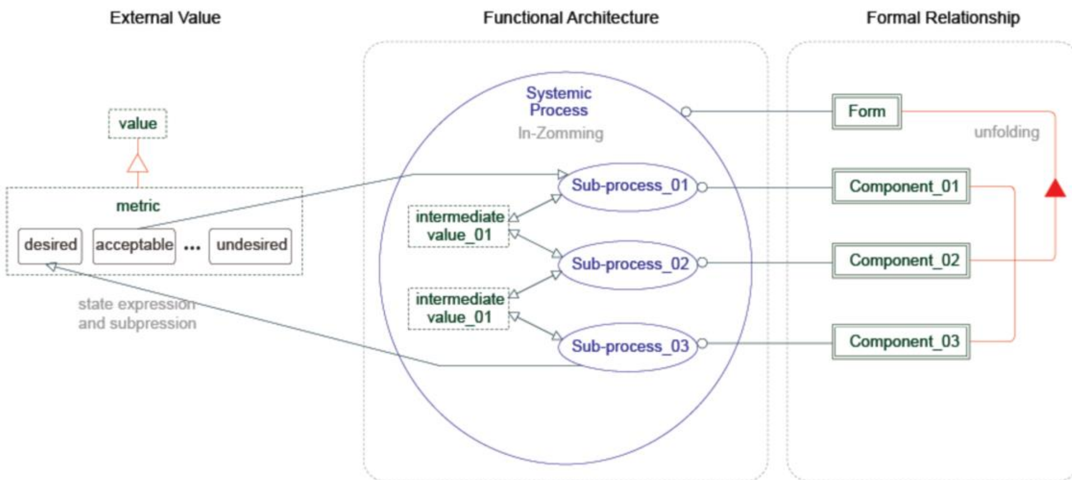

Figure 4.2.1d Complexity Management in OPM:
(left to right) states expression/suppression, processes in-zooming, and structural relationship unfolding.

The preceding sections had motivated the use of OPM diagram as the representation for multi-objective street design. While many theories and concepts from the existing literature in design research and systems engineering had been discussed, it is crucial to elaborate key components in the design representation in the following definitions.

Value: an objective or a desired state of affair distilled from an ill-defined problem space. Value is what the design tries to deliver or contribute to significantly by performing its function. Values can be simple, e.g., the *safety* of a street, or compound, e.g., *a vibrant street with multimodal transit options*.

Metric: a metric serving as a proxy for the value, also the primary operand of the designed system, e.g., *traffic capacity or stormwater peak flow*.

Primary function: what the designed system does which justifies its existence, equivalent to a "primary externally delivered function".[68] For instance: *reducing stormwater peak flow*.

Function: equals "process plus operand"[69], or the transformation plus the object being transformed. Function is a more general description encompassing both primary functions and other internal functions. For instance: *narrowing (process) driver's visual field (operand)*.

Functional Architecture: "function plus functional interaction"[70], or a set of function and a set of functional relationships describing their interactions.

Form: the design solution which persists for a stable period[71]. For instance: *a bicycle infrastructure*.

Formal Architecture: a set of "formal relationship"[72] describing how components of the form are related to one another. For instance, a bicycle infrastructure is *composed of* designated cycle lanes, bike corrals, bike boxes and bicycle-specific traffic signals.

Context: The environment in which the system exists and interact with. The context can also be modeled as functions and forms. For instance: *an over-capacity roadway* is the contextual which enable the designation of bicycle lanes.

Value Delivery Strategy (VDS): A representation of the design problem framing; a mapping from value to form, i.e. how values are delivered in a design. This includes the *framing*—the *metrics* defining the problem scope and the *functional architecture*, as well as the form which implements proposed design frame.

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[68] Crawley, Cameron, and Selva, System Architecture. p. 83.
[69] Ibid. p. 84.
[70] Ibid. p. 98.
[71] Ibid. p. 54.
[72] Ibid. p. 63.

We can observe that the proposed value delivery strategy maps closely to “design-abductive” thinking and its encoded framing (Figure 3.3a). The *Value*, unfolded as the proxy *Metrics*, correspond to the “Outcome”; the *Functional Architecture* in a VDS is equivalent to the “how”; the *Formal Architecture* can be understood as the “what”. The prescription of *Functional Architecture* necessarily constraints the possible options of *Formal Architecture* which in turn enables the functionality of a design. In short, the “frame” of the design problem, as studied by Schön, can be encoded into the choice of value and its interpreted metrics—the selection of a set of entities from the problematic context; and the prescribed functions of the design—a coherence imposed on the search of solution.

4.2.2 Bayesian Probabilistic Inference

The thesis has hitherto demonstrated a simple lane narrowing design strategy represented as a system architecture. However, a conspicuous issue yet to be addressed is that such representation is entirely deterministic and fails to reflect uncertainties inherent in real world planning. These include exogenous factors arose from changes in regulatory, economic, technological, and environmental sectors as well as endogenous feedback within the structure of an urban system. A design representation bearing useful resemblance to reality should reflect uncertainties such that its underlying assumptions can be validated or updated as new evidence emerges.

It is nothing new in updating one’s believes given newfound evidence. Advances in fields of science, engineering and medicine depend on their ability to regularly validate and update existing theories and models. Discovered and published by English mathematician Thomas Bayes in 1763, Bayes Theorem provides a mathematical model for belief update in light of new evidence and quickly became one the most fundamental formula in the study of probability.[73]

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[73] “Bayes’s Theorem | Definition & Example | Britannica.”

Bayes' theorem[74] (equation [1]) articulates a simple yet powerful relationships between two conditional probabilities: a hypothesis given its evidence and vice versa. *P(E|H)* represents the likelihood—the probability of seeing the evidence given a hypothesis is true. *P(H|E)* describes an *a posterior*—the probability of a hypothesis being true *given* relevant evidence. The remaining terms simply describes the unconditioned probabilities where *P(H)* is the probability of a hypothesis being true and *P(E)* being the probability of seeing relevant evidence.

$$P(H|E) = \frac{P(E|H)\,P(H)}{P(E)} \qquad [1]$$

If Bayes theorem had provided us a mathematical model for updating a single belief, Bayesian Network then generalized it to a network of beliefs. Developed by computer scientist and philosopher Judea Pearl, Bayesian Network is a Directed Acyclic Graph (DAG) used to describe the probability distribution across an arbitrary set of random variables. The graph $G = \{N,\ E\}$ denotes a set of nodes and the edges linking the nodes. Each node has a conditional probability given its parent, while each edge points from a parent node to their children nodes. Bayesian Network had found its use in many forms of causal reasoning, such as diagnosis (deriving causes from symptoms) and predictions (deriving effects from causes).[75]

Equation [2][76] formally describes the joint probability across a set of random variables X_1 to X_n as the product ("Π" notation) of each variable's conditional probability given its parents. The equation encodes an important underlying assumption —given the probabilities of its parent nodes, a node is conditionally independent of its non-descendants in the graph.

$$P\left(X_1 = x_{1,\dots,}X_n = x_n\right) = \prod_{i=1}^{n} P(X_i = x_i|Parent(X_i)) \qquad [2]$$

[74] Ibid
[75] "Bayesian Network | SpringerLink."
[76] Pearl, Probabilistic Reasoning in Intelligent Systems.

In the following section we will explore ways to incorporate Bayesian inference into the representation of the *Lane Narrowing* strategy. The first step is to view our current representation in terms of components of a Bayesian Network. Recall that Bayesian Network is a DAG. Each node stores the conditional probability given its parent nodes. Each edge resembles the dependencies of each child node on its parent nodes. The OPM diagram of *Lane Narrowing* (Figure 4.2.1b) is essentially a graph $G = \{N, E\}$ where nodes include the objects, processes, and states while the edges are the structural and procedural links which connects the nodes. Edges in a Bayesian Network typically encode "causal" linkages,[77] thus one can view the prescribed procedural and structural links as implicit "causal" linkages between nodes. For instance, *Reducing (node)* occurred because *DoT (node)* had enabled it; likewise, *Lane width (node)* is changed by the process of *Reducing (node).* Thus, we can directly convert every OPM procedural link into a directed edge in a Bayesian Network.

On the other hand, the bidirectional structural links as shown in the OPM ontology diagram (Figure 4.2.1a) needs a minor modification for each bidirectional link essentially create a two-node-cycle. In general, Bayesian Network breaks down in the presence of a cycle, i.e., when the nodes and links form a directional closed loop. To mitigate this issue, a trivial solution is to choose a single direction in a consistent manner across all structural links. For instance, the *generalization-specialization* link between *Safety* and *Vehicle Speed* can be read as *Safety generalized by Vehicle Speed* or as *Vehicle Speed specializes Safety*. We can safely discard one direction and maintain a semantic coherence. Shown in Figure 4.2.2a, all bidirectional structural links can be simplified as unidirectional links that points from *parts* to *whole*; from *specialized* to *generalized*; from the *characters* to the *characterized*; and from *instances* to *classes*.

[77] Mathematically, Bayesian Network does not imply causation. It merely captures conditional independence, which nevertheless had been colloquially referred to as causal relations because the model implicitly assumes that a variable no longer interacts with other variables, once its parents ("causes") have been given.

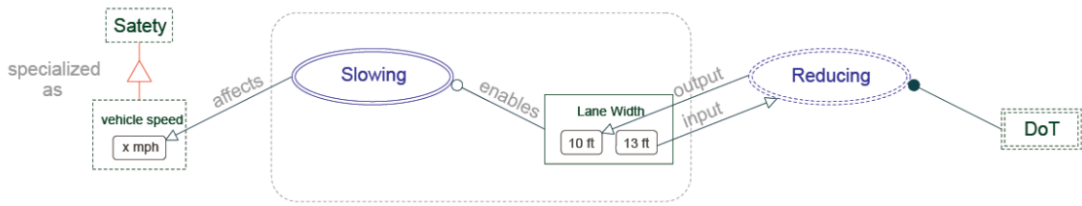

Figure 4.2.2a
bi-directional to unidirectional link

With the translation of both nodes and edges in place, we are ready to convert the OPM diagram as a Bayesian Network. Figure 4.2.2b shows an initial attempt at such conversion. Immediately we see an occurrence of another cycle, between *Lane Width* and *Reducing* as connected by the *input* and *output* procedural links. Again the cycle obstructs Bayesian inference for the product of conditional probabilities (Equation [2]) is trapped into the perpetual multiplication between $P(\text{Reducing} \mid \text{Lane Width})$ and $P(\text{Lane Width} \mid \text{Reducing})$. In Figure 4.2.2c, the author attempted two alternative OPM expressions to eliminate the problematic cycle. The left pair of diagrams shows an explicit representation of the states of *Land Width* in the OPM diagram and the elimination of cycle in its Bayesian Network counterpart. Alternatively, in the right pair of diagrams, *Lane Width* is treated as the result of *Reducing*, which is now *characterized by* a reduction *Width*. This also eliminates the cycle in the Bayesian Network.

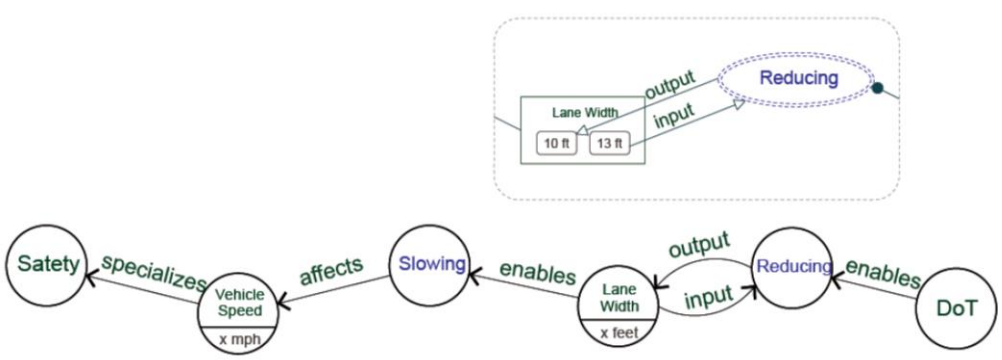

Figure 4.2.2b
Initial attempt of converting OPM model to a Bayesian Network

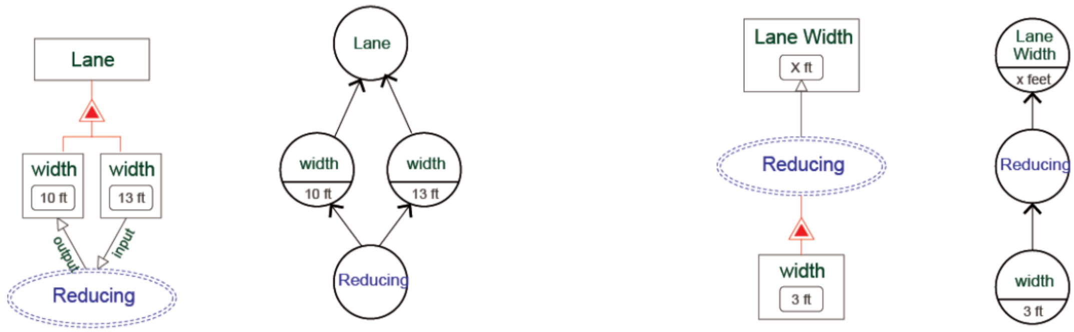

Figure 4.2.2c
Cycle Elimination Attempts from OPM Diagram to Bayesian Network

Thus far it appears that we have addressed the issue of cycles in converting OPM diagram into Bayesian Network. Yet, the derived Bayesian Network make little semantic and logical sense. For instance, the left pairs of diagrams represents $P(\text{Lane }|\text{width} = 10\text{ft}, \text{width} = 13\text{ft})$, denotes the probability of *Lane* occurring given the joint probability of two *Widths*. While it is meaningful to discuss the probability of a 10-foot-lane or a 13-foot-lane, it is illogical when the likelihood of a *Lane* depends on its *Widths* being simultaneously 10 feet and 13 feet. The right pair of diagrams represent a $P(\text{Lane Width }|\text{Reducing})$, i.e., the probability of an unknown *Lane Width* given *Reducing*. The issue here is that *Reducing* has no dependencies on the initial *Lane Width* and thus devoid of a subject (i.e., what is being reduced?).

A key insight derived from the above experiment is that *Lane Width* is fundamentally a temporal variable which a standard Bayesian Network fails to recognize. For example, the *Width* of a *Travel Lane* persists until it is altered by an external force and thus inappropriate to be modeled as a random variable. To accurately represent the temporal dimension in the design strategy, the author looked, instead, into Dynamic Bayesian Network as an alternative model for capturing uncertainty.

Dynamic Bayesian Network (DBN) is distinguished from its standard counterpart by the explicit representation of multivariate time series.[78] In DBN, time is represented as a series of discrete steps. Temporal nodes $X^{(t)}$ persist in each time step, while edges can stay within

[78] Koller and Friedman, Probabilistic Graphical Models. p. 202.

the same time step (non-temporal dependencies) or across time step (temporal dependencies). DBN represent a time trajectory of arbitrary length using a pair of networks (B_0, B_t), where B_0 is the Bayesian Network over initial variables $X^{(0)}$ and B_t, the transition network which connects any two timesteps, spanning between $X^{(t)}$ and $X^{(t+1)}$.[79] It does so based on two important assumptions: *Markov assumption* where the next timestep is conditionally independent of all other time steps given the current time step; and *time invariant assumption* where the transition network B_t is shared (i.e., identical) across all transitions.[80] With these assumptions in mind, we can represent a joint distribution of a set of random variable over an arbitrary trajectory in Equation 3. The joint distribution is now a product of conditional probabilities of each node given its parents at each time step. In this thesis, a two-time-slice Bayesian Network (2TBN) is sufficient to describe dynamics in a design strategy.

$$P\left(X^{(0:T)}\right) = P\left(X^{(0)}\right) \prod_{t=0}^{T-1} P\left(X^{(t)} \mid Parent\left(X^{(t)}\right)\right) \qquad [3]^{81}$$

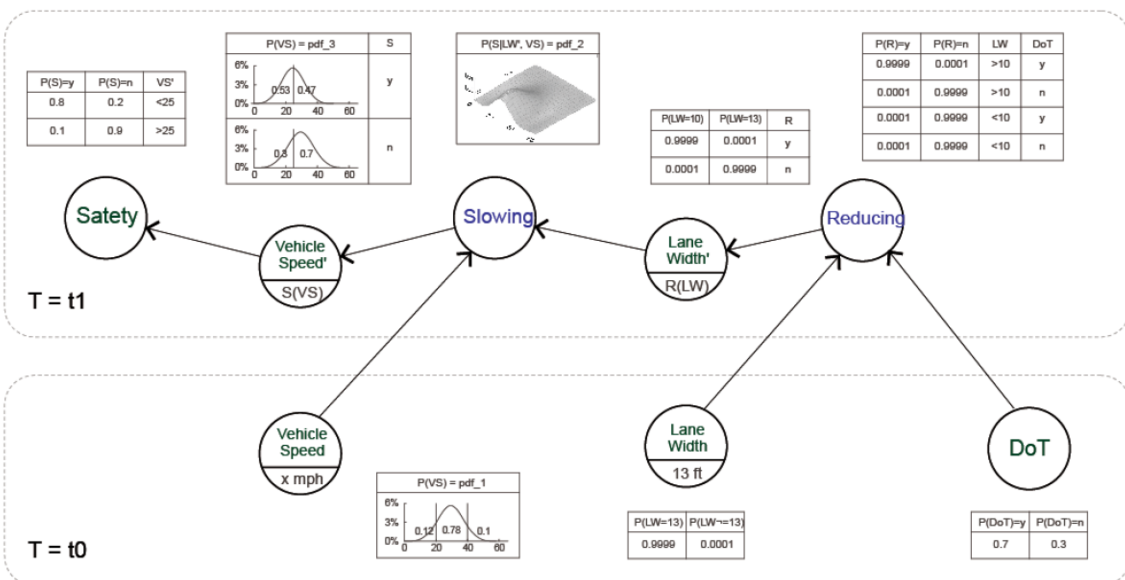

Figure 4.2.2d
Lane Narrowing Represented as a Bayesian Network

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[79] Ibid. p. 204.
[80] Ibid. p. 202-205.
[81] Ibid. p. 203.

Now, let us represent the *Lane Narrowing* strategy as an unrolled 2TBN (Figure 4.2.2d) by converting *Lane Width* and *Vehicle Speed* as temporal nodes. We use a superscript to distinguish the initial *Lane Width* $^{(0)}$ from the transformed *Lane Width* $^{(1)}$. The same notation applies to all temporal nodes. We observed that no cycle is present in the network. Additionally, the relationships between transformed objects and their transforming processes appears to be logically consistent with its OPM counterpart. For instance, the probability of *Reducing* depends on *Lane Width* $^{(0)}$ and *DoT*, whereas the transformed *Lane Width* $^{(1)}$ depends on *Reducing*. In this strategy, *Lane Width* is modeled as a discrete variable of value 10 or 13 feet. Thus, the probability of *Lane Width* $^{(1)}$ can almost be modeled deterministically for it will either be reduced to 10 feet or remained at 13 feet. But what if *Lane Width* is an unknown variable that depends on an additional parameter of *Reducing*, e.g., *Reducing* by *X feet*? Clearly, we should not confuse the result of a transformation with the probability of the result given its transformation. To facilitate these two separate types of computation, processes such as *Reducing* and *Slowing* need to store an additional function to yield the actual result of the transformation, external to the Bayesian Network.

Before inference is performed over the joint distribution, the network needs to be initialized according to values listed in Figure 4.2.2e. In addition, each node (Figure 4.2.2d) needs to store a conditional probability table (CPT) should it be discrete, or a conditional probability distribution (CPD) should it be continuous. *Vehicle Speed* $^{(0)}$ has a normal distribution with a mean of 52 mph and a standard deviation of 7 mph. The function of *Reducing* is modeled as a deterministic function that reduces *Land Width* by 3 feet, while *Slowing* is naively simplified as a function reducing the mean of the input distribution by 5 mph and its standard deviation by 1 mph.

```
VARIABLE INITIALIZATION

Vehicle Speed := pdf_1
Lane Width := 13 ft


CONDITIONAL PROBABILITY
PARAMETER INITIZLIATION

Safe Speed := 25 mph
width threshold:= 10 ft
```

```
PROCESS FUNCTION INITIALIZATION

Reducing := reducing(args, params)
Slowing := slowing(args)

Function reducing (args, width=3'):
   lane_width = args
   Return lane_width - width

Function slowing(pdf):
   Return transformed pdf
```

Figure 4.2.2e
Bayesian Inference Initialization

Let the following be our query:

> In a 13-foot-lane urban street with mean traffic speed of 52 mph and a standard deviation of 7 mph, what is the probability of the street becoming safe given that the City's Department of Transportation reduces the lane width by 3 feet? If there an 80% chance of the street becoming safe should traffic speed fall below 25 mph?

Or mathematically, what is

$$P(Safety = yes \mid Vehicle\ Speed \sim N\ (\mu = 52, \sigma = 7), DoT = yes, Lane\ Width = 13)?$$

The inference operation consists of two steps. Firstly, the unknown variables are computed based on functions stored in processes responsible for variable transformation. For instance, *Reducing* takes *Lane Width* $^{(0)}$ and yields *Lane Width* $^{(1)}$ of 13 feet. *Slowing* takes the initial distribution of *Vehicle Speed* $^{(0)}$ and yields a new *Vehicle Speed* $^{(1)}$. Next, we compute the joint distribution using Bayes Theorem (Equation [1]), DBN's joint distribution (Equation [3]) and derived the conditional probability as illustrated in Equation [4]. For simplicity, the author decided to discretize *Vehicle Speed* $^{(0)}$ into the domain of [0-20), [20-40), and [40-60) mph, and the resultant *Vehicle Speed* $^{(1)}$ into $<=$25 and $>$25 mph, with 25mph being the initialized safety speed limit. Another discretized variable—*Slowing* is modeled as a conditional distribution over *Vehicle Speed* and *Lane Width*. The computation yields an exact inference using a method called Variable Elimination. The result of the query $P(Safety = yes \mid DoT = yes, width = 3)$ is 0.5045, which is approximately 50% chances.

$$P(Safety = y \mid DoT = y, Lane\ Width = 3) \quad [4]$$

$$= \frac{P(Safety = y, DoT = y, Lane\ Width = 3)}{P(DoT = y,\ Lane\ Width = 3)}$$

$$= \frac{\sum_{VS^1}\sum_{Sl}\sum_{VS^0}\sum_{LW^1}\sum_{R} P(Safety, \dots, DoT)}{\sum_{Safety}\sum_{VS^1}\sum_{Sl}\sum_{VS^0}\sum_{LW^1}\sum_{R} P(Safety, \dots, DoT)}$$

$$P(Safety, \dots, DoT) = P(Safety|VS^1)P(VS^1|Sl)P(SL|LW^1, VS^0)P(LW^1|R) \\ \times P(R|DoT = y, LW^0 = 3)P(VS^0)P(DoT = y)P(LW^0 = 3)$$

The estimate is not optimistic. Yet, it merely reflects the uncertainty as specified in both the design strategy and its context. A sensitivity analysis—used to identify variables having the strongest impact on the outcome variable—indicates that the conditional probability $P(SL|LW1, VS0)$ and $P(VS1|SL)$ of node *Slowing* and *Vehicle Speed* *(1)* as the two biggest contributing factors. The implication is that the design strategy should place emphasis on obtaining approvals of *DoT*, who facilitates the process of *Slowing,* as well as ensuring that the initial Vehicle *Speed* *(1)* is within the favorable range. Still, in the current joint distribution, little over half of the times might we achieve the proposed safety objective. Perhaps it simply signals spurious probability distributions assumptions in the model and suggests the need for its validation and update. With Bayesian inference, we can articulate uncertainties in both the design and its context, as well as validating and updating our assumptions to reflect evidence or changes in the real world.

4.3 Application Design

The proposed database application consists of mainly two types of operations: the first one pertains to the insertion, retrieval, and update of design strategies while the second one focuses on the analysis of Value Delivery Strategies (VDS). Constrained by time and resources, the thesis focused primarily on the second type of operation, including probabilistic inference given a VDS and the analysis of interactions between different VDSs. Demonstrated in detail in Section 4.2.2, a value delivery inference is a direct application of Bayesian probabilistic inference on a VDS, showing the likelihood of a strategy achieving its intent given the initial conditions under the specified constraints.

On the other hand, an interaction analysis between two different VDSs aims to unveil mutual influences that two VDSs can potentially have on one another. For instance, given two VDSs: one focuses on improving the quality of public transit by designating bus-only lanes, while another VDS focuses on promoting cycling by reducing obstructions and buffering existing cycling infrastructure. The form or implementation of both design strategies—a bus-only lane and a continuous and buffered cycling lane—hinges on the allocation of roadway spaces, thereby inadvertently tethered to one another in the same design. The example cited, contrived as it seems, nevertheless illuminates the challenges of integrating a broad set of intricately linked heterogeneous values in a complex and uncertain problem space.

The proceeding paragraphs walks through three types of VDSs interactions: *object-object*, *object-process*, and *process-process*, and formally defines the interaction analysis. It should be noted that these interactions analysis have not been implemented, but rather serve to elaborates the mechanism by which the proposed representation can allow for computational analysis that unveils their latent interactions.

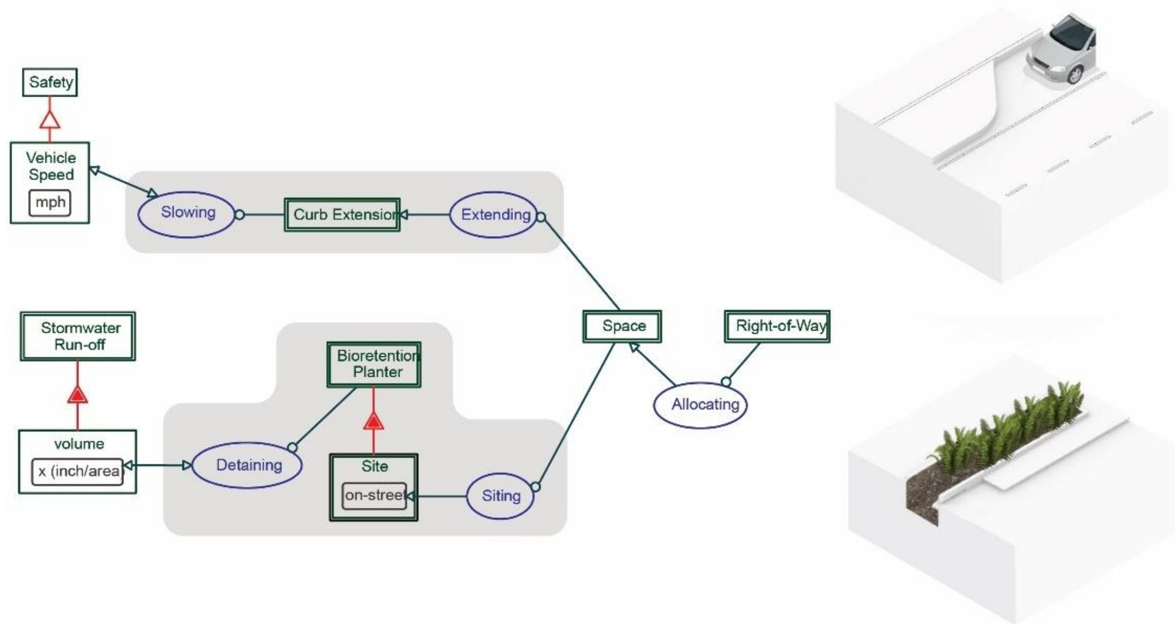

Figure 4.3a
Object-Object Interaction

The first type of interactions is the *object-object* interaction, which occurs when two VDSs are conditioned on objects that are structurally connected. This is often the most common interaction. Designs serving different objectives often compete for the same physical resources while in rare occasions the implementation of one design might inadvertently facilitate the implementation of the other. Figure 4.3a shows two VDSs, one proposes using curb extension to slow traffic speed while the other suggest mitigating stormwater runoff with bioretention planter. As their OPM diagrams suggest, both VDSs rely on mutually exclusive components of the *Right-of-way*, namely, *Roadway* and *Sidewalk*. While a *Curb Extension* converts *Roadway* into *Sidewalks*, a *Bioretention Planter* can be sited in the newly gained *Sidewalk* spaces. The interaction analysis suggests that these two VDSs are mutually beneficial, hence their driving values can be considered in concert in reframing of an integrated design strategy.

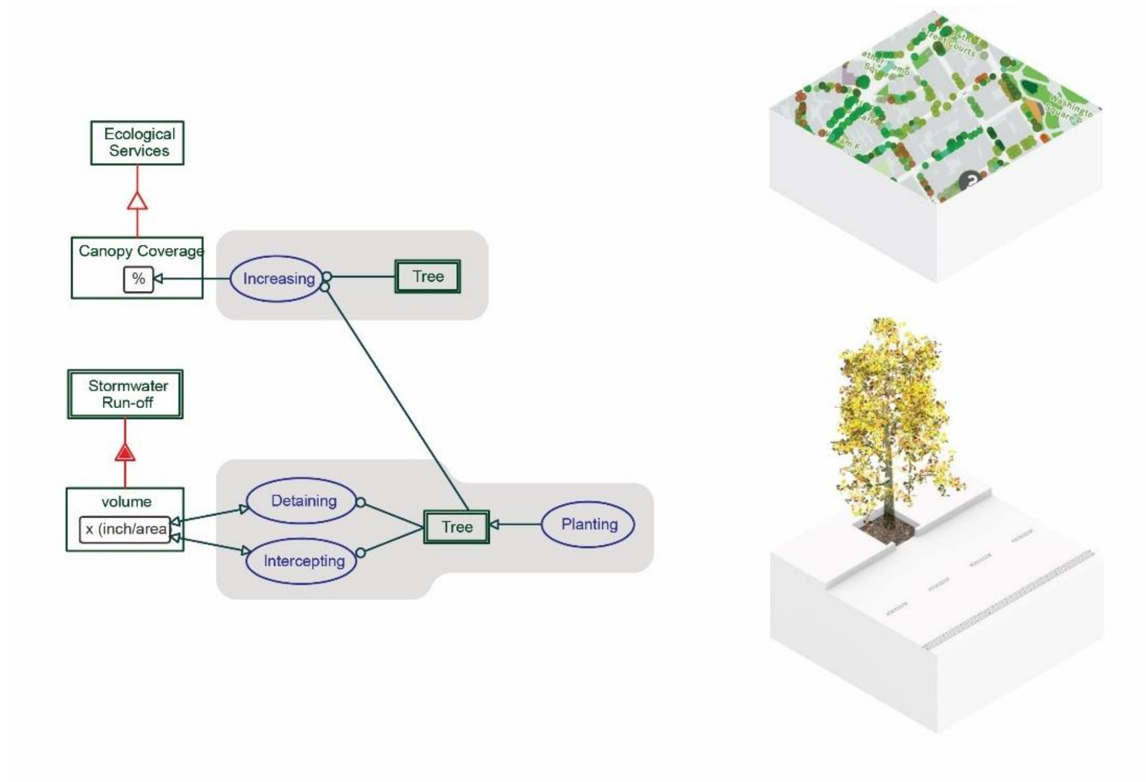

Figure 4.3b
Process-Object Interaction

The second type of interactions—the *process-object* interaction—can be further elaborated as either a process from one VDS affecting an object in another VDS or vice versa. In the first scenario, the process in a VDS is referred to as having *side-effects* beyond the scope of value delivery considerations. For instance, street trees can improve pedestrian comfort by facilitating the process of *Shading*. Depending on proximity and orientation, the same process of *Shading* might also benefit a nearby building by reducing its energy usage for cooling. In the second scenario, an object in one VDS facilitates a process in another VDS, i.e., performing multiple functions at once. Figure 4.3b shows that street trees can absorb and intercept airborne pollutants. Beyond the concern of improving air quality, the presence of street tree also directly increases the canopy coverage in a city. Thus, these *process-object* interactions also serve as the basis to inform an integrated framing—a positive coupling between pedestrian comfort and building energy reduction by means of shading or an increase in canopy coverage with considerations of runoff mitigation.

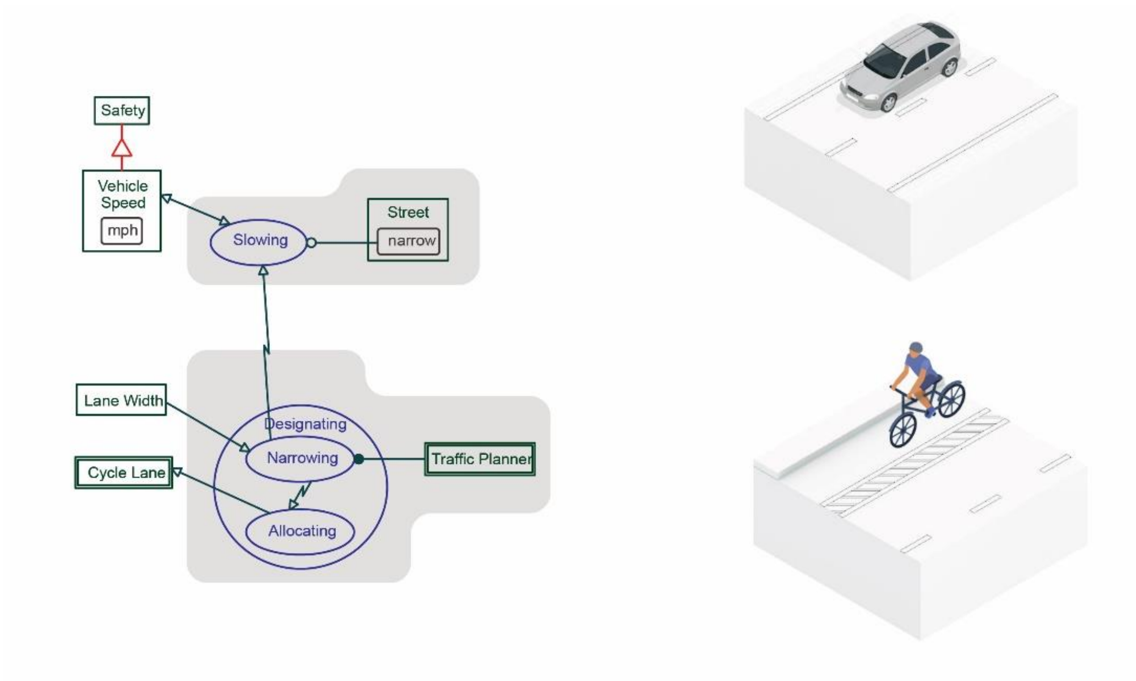

Figure 4.3c
Process-Process Interaction

The last type of interactions, also the most difficult to compute, is the *process-process* interaction, which involves processes from separate VDSs directly invoking one another. These invocations may occur in the following scenarios. One scenario depicts the processes (from two VDSs) naturally occurring in sequence. For instance, allocating a finite resource to one design solution necessarily reduces resource available to another. Figure 4.3c shows that designating a cycling lane inevitably leads to reduction in roadway width—a strategy frequently employed in the process of road dieting. In another scenario, one process serves as a subprocess of another and is automatically invoked when the main process executes. For instance, a city with the goal of enlarging its green canopy coverage will inevitably invoke the process of planting trees. These coupled processes from different VDSs, once again, shed light on the relationships between various value propositions, thus informing the next iteration of problem reformulation.

The interaction analysis thus shows, at least in the contrived examples illustrated, potentials in catalyzing an iterative design process not unlike the "co-evolution of both problem understanding and solution synthesis" discussed by Dorst and Cross—a process that is "solution-focused".[82] The VDSs proposed, in the absence of a comprehensive problem formulation, are essentially "solution-led" conjectures as means to inquire the problem space. The interactions unveiled by the analysis serve as the feedback between the formulated problem and the proposed solutions. Thus, they remain in flux as changes in various framings (value metrics and functional architectures) and their respective proposed implementations (formal architectures) propels one another's evolution in the process of design.

In addition to the unveiling of design strategy interactions as elaborated in the preceding passages, the analysis can further quantify the strength of the interactions via sensitivity analysis. Using the Dynamic Bayesian Network, a sensitivity analysis reveals the evidence variable whose changes have the most contribution to the uncertainty of the query variable. For instance, between the VDS that slows traffic speed with curb extension, and the VDS that mitigates stormwater runoff with bioretention planter (Figure 4.3a), we might be interested in finding out how changes in object-object interaction—the width of roadway and sidewalk—affects the probability of road safety and runoff mitigation. Or mathematically, $P(Roadway\ Width, Sidewalk\ Width)$ and its effects on the probability of the following value deliveries: $P(Safety \mid Roadway\ Width)$ and $P(Runoff\ Mitigation \mid Sidewalk\ Width)$.

[82] Nigel Cross, *Designerly Ways of Knowing* (London: Springer, 2006). Chapter 6.

5. Discussion

The preceding chapter had illustrated the mechanisms by which the proposed representation of Value Delivery Strategy (VDS) can unveils latent interaction between different value propositions. These latent interactions are indeed what Schön had referred to as the "back-talk"[83] from the problematic situation, only, in this case, the *actions* to be *reflected* upon and the *act* of *reflecting* have both taken on a collective dimension, leveraging diverse approaches in delivering heterogenous values. Forming the basis of new framings, such collective reflections *can* fuel the co-evolution of both problem formulation and solution synthesis. Nevertheless, they hinge on the effectiveness of VDS in representing both problems and design solutions, as well as in facilitating stakeholder interaction and communication—both of which are not without limitations.

5.1 Representation Limitations

The proposed graph database and its applications are largely theoretical and remained to be implemented, it is worth noting several foreseeable limitations. One limitation lies in the ontology of OPM, as the thesis has only demonstrated applications of OPM on contrived examples of street design. Without further experimentation, it remains unclear whether the systems modeling language of OPM can be generalized to represent more complex design and planning scenarios. Moreover, it might not always be possible nor appropriate to represent urban design as engineered systems, especially when they express tacit and nuanced qualities that defy explicit representations.

Another discernable limitation is the scaling of Dynamic Bayesian Network. As the design strategy become more sophisticated, the number of variables and the size of the network inevitably grows. As a result, the Conditional Probability Table (CPT) for a variable with large number of states or parent nodes can become infeasible to initialize. Moreover, variable Inference performed on a large Bayesian Network can be significantly bogged down by its

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[83] Schön, The Reflective Practitioner. p. 102-104

computation bottleneck. Similarly, a large model also increases the likelihood of cycles as the feedback in the system grow more complex. As mentioned in section 4.2.2, the presence of cycles effectively breaks the Bayesian Network. A possible workaround might be to increase the level of abstraction to eliminate irrelevant design details and reduce the number of variables. Yet, there is a cautious trade-off between the parsimony and accuracy of the representation.

Other technical limitations can occur during the interaction analysis. One such issue is Entity Resolution, namely the consolidation of differing records corresponding to the same real-world entities. This can stem from differences in naming conventions. For instance, in Figure 4.3a, the object *Space* might be interchangeably named *Width* or *Breadth*. Both preserves the semantic precision of the design strategy, but inadvertently makes the interaction analysis between VDSs more troublesome. An even thornier problem results from entities modeled at different scales and granularity. Currently, it is unclear how the database might resolve similar or identical objects represented at differing levels of abstraction.

5.2 Affordance Limitations

Although the design of the User Tier had yet to be explored, the author has speculated challenges in making the database application accessible to stakeholders from a variety of domains. The hinderance of affordance can stem from the overhead of adopting the language of OPM and Bayesian Network, both of which are ingrained in the proposed design representation. Despite OPM being a relatively lean modeling ontology, the need for an explicit representation of objects and processes might not only bring onus to the modeler but also introduce tacit biases in the design representation. For instance, they might inadvertently omit details that are hard to explicate but nonetheless play a crucial role in the context of the design. Similarly, Bayesian Network can be counterintuitive as it needs to convert every variable into a conditional probability distribution. For certain design variables probability distribution may not always be pertinent or appropriate, whereas forced conformity only widens the gap between representation and reality. The potential friction in adopting the proposed representation has also highlighted the importance of a proper user interface which can hide unnecessary details and complexities otherwise burdensome to a stakeholder's workflow.

On the other hand, the thesis was built on the untested premise that different domain expertise can be projected onto a shared representation of design strategy. Without empirical studies, there is little evidence in support of the feasibility and effectiveness of such shared design representation. Furthermore, whether the interaction analysis can truly lead to a more salient collective framing remains little more than a speculation. After all, the reality of collective decision making is extremely complex. Valkenburg and Dorst acknowledged the challenge of frame communication amongst even experienced professionals, for frames are only productive when they are incorporated into the collective thought process.[84] Foresters also observed that the salience of any computer model is rooted in its ability to relate to and improve mental models of users.[85] Only experimentations can tell whether constructive problem framing can aid stakeholders in overcoming conversation breakdown and to see past deeply entrenched biases.

[84] Valkenburg and Dorst, "The Reflective Practice of Design Teams."
[85] Forrester, "Systems Dynamics and the Lesson for 35 years." in *A Systems-Based Approach to Policymaking*, eds. De Greene. p. 219

6. Conclusion

In this thesis, the author explored a novel approach in representing urban street design strategies that encodes the framing of their value propositions. Combining techniques from system engineering, probabilistic inference, and graph data modeling, the author attempted to address the multi-objective, complex and uncertain nature characterizing issues in urban design and planning. By representing and analyzing a set of simple albeit contrived street design strategies, the author have demonstrated the potential of such representation in unveiling latent interactions between different value propositions, synergistic or conflicting, thus informing the reformulation of the design problem.

6.1 Contribution

This thesis has made the following contribution:

- Demonstrated the potential of using system modeling language—OPM in representing design strategies and encoding their value framing.
- Demonstrated the possibility of incorporating Bayesian inference into OPM diagrams to reflect the uncertainties inherent in urban design and planning while providing a mechanism for evidence-based assumption validation and update.
- Demonstrated that, in a multi-objective design setting, simple design strategies can be represented such that their interactions can be analyzed to inform the reframing of design problems.

6.2 Future Work

The research on the proposed design knowledge representation and database application had merely begun. The next immediate step would be to complete the data pipeline bridging OPM, Bayesian Network, and Graph database, facilitating seamless read-write operations. A graphical user interface for design modeling in OPM can offer more intuitive experience in contrast to modeling programmatically. Further studies and testing in user interface and interaction will be pertinent to development of the application. The proposed representation should also be tested in a wide range of urban design scenarios while relying on empirical design and performance data for calibration and validation.

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Figure List