Agent architectures in building performance simulation: a review of current methods

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Abstract
Building Performance Simulation (BPS) has made attempts at using Agent-Based Modelling (ABM) techniques to validate, calibrate or enrich existing modelling techniques. The methods thus far have relied on a representational architecture that captures basic demographics and rudimentary behaviour concerning the interactions with mechanical equipment. This paper reviews the state of the representation of agents in agent modelling as a part building performance simulation and examines what can be learned from the human sciences to improve these models and demonstrates how to choose an ABM architecture for common use BPS use cases.

Key Innovations
- Provides a cohesive description of how to represent agents as a part of ABM.
- Identifies opportunities for development in current simulation environments.
- Provides a framework to consider when selecting how to construct an agent representation.

Practical Implications
This paper provides building performance practitioners a comprehensive review to the field of agent-based modelling and gives them the ability to question and select the type of agent architecture to support diverse investigations in the built environment.

Introduction
The work of recent decades to quantify the performance of buildings has focused on a world view where buildings are exclusively physical objects. This disciplinary ontology has led to an epistemology that understands buildings and their functions in similar physical terms, via complex descriptions of heat and energy flows through matter, or the operations of classical machines (i.e., HVAC systems) (Augenbroe 2019). The rapidly changing landscape of working and occupancy habits forces the assumptions into question and places energy usage as a human sciences problem as opposed to a physical and mechanical one. The assumption that energy consumption is only a matter of physical systems, instead of a social phenomenon, has been routinely criticized for being unable to sufficiently account for the energy consumed by real buildings (Hamburg et al. 2020; Turner and Frankel 2008) and remains unaddressed. While a portion of the variance can be explained by the difference between real conditions and ideal assumptions, much of it can be accounted for by occupant behaviour (Hensen and Lamberts 2019).

Occupant behaviour is a variable that is not well represented within Building Energy Modelling (BEM). These models represent occupants based on presence, while missing other aspects, such as the preferences of an agent within a space. Occupants have agency over spaces inhabited and exist in a cyclical relationship that space, able to alter the space, themselves, or both. This cyclical relationship is linearized into a unidirectional relationship in which the occupant modifies the state of a given environment, but never the other way around. BEM’s failure to capture this behavioural aspect leads to significant misrepresentation, such as Turner’s (2008) 32% variance between simulations and observed real-world usage in non-residential buildings. The idea that an agent cannot modify themselves or modify their places within a building as desired, reinforces a curated view of buildings that only presence drives demand, and that behaviour does not change that demand curve.

Agent Based Models (ABMs) have been proposed as a means of addressing this issue and adding the necessary human dimension (Epstein and Axtell 1997; Gilbert and Troitzsch 2005). Yet, within the epistemological model of Building Performance Simulation (BPS) agents still serve to construct a framework that does recognize the activity of those within beyond their interactions with physical systems. We argue that this incomplete view, especially within ABMs, creates an ontology that will continue to struggle to understand buildings for which occupancy is itself the purpose of buildings, as it fails to capture the diversity of experience and therefore activities that drive behaviour within, and thus the variance between simulated results and real outcomes, or the so called “performance gap” (Sun 2014).

Changing patterns of labour and occupancy towards a more distributed mode (The Bureau of Labor Statistics 2018), accelerated by events such as COVID-19 (Davidson 2021), create a real need to overcome this blind spot within the model view (Davidson 2021). The gap in our understanding of the effects of occupant agency within the built environment and how this agency goes on to influence the energy demand of buildings will only drive the gap wider in time.

This paper provides a review of the current state of the art in ABM as practiced in BPS and concerning BPS in design practice. Given the fragmented conditions of...
discourse around ABMs in BPS, this review focuses on highlighting concepts for understanding how occupants and their behaviours are represented within ABMs and provide an entry point for understanding the construction, limitations, potentials. This review aims to aid researchers in selecting a suitable architecture for study purposes. This paper is organized into four sections. The first introducing the methodology the authors took in preparing the review. Second, the review of the literature itself. Third, a synthesis of what is presented within the review. Lastly, a conclusion that briefly covers major use cases, such as energy modelling, and how to select an architecture for that purpose and finally, laying out a path for future work.

Methodology
This review began by a database search through ProQuest and Web of Science for papers that included the terms “agent-based modelling”, “building energy modelling” and “design” to begin with. This search resulted in a total of 1,422 results spanning the years 1980 through 2020. From this set 1100, or 77.4%, have been produced since 2015, indicating a rise in popularity.

These papers were filtered based on specific criteria. First, that the paper should be after 2015 as these papers represent, in the opinion of the authors, the best representation of the state of the art. If the is from before 2015 then the paper should represent a significant theoretical contribution to the field. This resulted in a total of 295 total references for review of which 66 have been included in this review. For a comprehensive review across a broader epoch of ABMs in for BPS see (Berger & Mahdavi, 2020).

Literature Review
The review is structured into four themes. Starting with history, introducing how ABM concepts arose, and then introduce ABMs as a method of conducting research in the human sciences. The authors then discuss BEM topics specifically. Firstly, the ways occupants are represented within energy models currently and finally, the ways ABMs have been used within BEM.

ABM represents as much a mindset, a way of considering problems, as much as a set of specific technologies and techniques. It is a methodology that looks to the smallest possible unit for answers assuming that it is from these finite units that higher order patterns emerge (Bonabeau 2002). ABMs are a methodology for investigating non-linear, dynamical systems, specifically the ones for which patterns of collective and individual action will alter the overall system at large (Gilbert and Troitzsch 2005). It is a fundamental change in the assumptions of the method of investigation and therefore a change in the way of asking questions and understanding the results (Tufte 2020). This is a method of investigation that it is more than just their presence alone that drives the phenomena being investigated (Chapman 2017).

ABM Architecture in the Human Sciences

The human sciences (sociology, anthropology, planning etc.) served as the genesis for study of complex social systems in a computational manner. The motivation was to expand the understanding of complex human systems and the motivations could be considered as (1) checking well established numerical models (2) compliment existing models, or (3) serve as a replacement for numerical models for intractable social problems (Axtell 2000). ABMs serve as a bridge between disciplines, such as when a research topic regards both institutional and individual actors (Axelrod 2006), or when there is an indeterminate dynamic factor (such as the social field or cognition) that cannot be explained purely by way of randomness (Gilbert and Troitzsch 2005).

A real actor has beliefs about their environment, desires about how they wish pursue tasks and acts in accordance with intentional plans (that are not necessarily economically rational). Where discrete models rely on this notion of a normative idea, agent models attempt to move beyond the rational agent and towards something that captures the messiness of the real. ABMs have been deployed in trying to unwind this messiness in concrete investigations, where the behaviour of one might have large, non-random, but also, not easily modelled, impacts on those around them. This has manifested in fields such as economics, transportation, and planning (Traine 2009). The ABM methodology is not constrained to pure rationality and is used in, for example, disaster modelling where the rationality of the actor may be compromised in part or whole (Esmalian et al. 2019; Luna-Ramirez and Fasli 2018; Shendarkar et al. 2008). This makes ABMs a flexible solution for modelling people, allowing for constraints to be added or relaxed.

In broad strokes we can define agent architectures within the human sciences as falling into one of two categories: Reactive Agents (RA) and Intelligent Agents (IA). RAs respond to the conditions of their immediate environment. While they can display social behaviour, they are ultimately reacting in a self-interested way to the resource availability in their environment. Epstein and Axtell’s “Sugarscape” stands as an early, sometimes problematic, but easily understood example of RA methods in which simplified agents were able to demonstrate societal stratification based on the unequal distribution and access.
to resources (Epstein and Axtell 1997). The simplified actions of these agents make it well suited for problems of economics, or in situations where the options are limited, but will root solutions in a notion of resource competition (Crociani et al. 2015).

The category of IAs are agents that attempt to go beyond simple mammalian reactivity to capture the complexities of cognition. This means that agents further react to both the environment (including other agents) and themselves. IAs can be further categorized by the conceptual approach they take towards the simulation environment. Cognitive agents are inspired by human cognitive processes approaching modelling from a more biological and neurological way. This architecture views perception and response to an external physical stimulus (Caballero, Botía, and Gómez-Skarmeta 2011). The other attempts to instead rely on the internal set of beliefs, desires and intentions of agents to approach the problem. This is a philosophically inspired stream based on work Bratman (1987) on intentionality and agency and later formalized into systems of modal logics by Rao and Georgeff (1995). This Belief, Desire, Intention (BDI) methodology is unified around a specific trinity with significant research behind this concept and is not fragmented in the same way as cognitive methods (Adam and Gaudou 2016). BDI architecture differs from the cognitive type by dealing primarily with symbolic interactions between humans and ways people articulate and communicate concepts to others. BDI agents have the advantage of producing easily interpretable and applicable results that facilitate higher degree of correspondence between simulations and descriptive observations of domain specific “common sense” evidence (Edmonds and Moss 2005).

**Occupancy Schedules**

Current methods in practice for occupancy models make use of deterministic schedules as a proxy to determine the occurrence of an event. Research in recent years, by groups such as Annex 66, have moved past this limitation, but have not had significant penetration into working practices (Deru, 2017). This reduces the impact of occupancy to density, active metabolic function and the presumed induced demand for a given programmatic specifications (Fadzli et al. 2013). This method treats occupants as having a scalar relationship with the performance of the overall system since occupant metabolic function produces heat, they operate lights and other equipment etc. (ASHRAE, 2016). Functionally, occupancy schedules act in a way as a type of rational agent simulation that assumes perfect rationality. This produces a representation of occupants as a flat 2D representation of population ratios across time intervals, which can be directly applied in building physics equations or directly to other vectors for which occupancy is a component (Webber et al. 2004) reducing out all notions of agency itself.

This representational methodology struggles to capture the diversity of occupants themselves. The varied methods of constructing occupancy schedules from observational methods (Davis and Nutter 2010), to GPS enabled travel demand surveys (Rakha, Rose, and Reinhart 2014), to sensor driven methods (Duarte and Rieger 2013) all still only capture if an occupant is within the building or not. These methods all are challenged by inherent bias. Travel demand methods suffer from double counting, and thus over representation of certain characteristics within the data (Erhardt and Rizzo 2018).

None of the methods though accurately capture demography. Occupants as a group are more diverse than schedules can represent and are therefore rendered as a singular monolith (Chang and Hong 2013).

Occupancy schedules, while a useful representation for the modelling of mechanical systems, do not go further into how a space is used and how that usage places demand on a mechanical system. The schedule model cannot explain differences in behaviour or how those differences impact the systems. Rather it creates a monolithically defined population that exhibits an idealized model of rational behaviour (Zaraket et al. 2015). Despite this, using occupancy schedules as surrogate representations is a key input for modelling building energy (Crawley et al. 2001). This remains true even in circumstances where the diversity of occupants and behaviours becomes crucial, such as at the urban scale where Urban Building Energy Modeling (UBE) relies on occupancy schedules (Reinhart and Davila 2019).

**ABM Architecture in Performance Simulation**

ABMs in BPS are used primarily to enrich existing occupancy schedules with data concerning how occupants use a building or interact in an urban area (Chang and Hong 2013). These enriched schedules attempt to, describe more accurately the temporal and spatial diversity of occupants (Luo et al. 2017). ABMs can also represent the effect of both social and physical space on an actor, and the effects that these have recursively on the agents. These come at the expense of the fact that creation of a robust model has high computational cost.

ABMs within BPS are fragmented and fractured and propose a multitude of approaches, frameworks, environments and tools. Between these though there are commonalities within the literature concerning the overall description of agents and the data architecture for how these agents are presented. It is worth reviewing these commonalities to develop a view of the different possible agent architectures available to practitioners.

Simulation involving agents begins with describing the population, the behaviours of that population and the feedback systems that induce behaviours. Since ABMs describe non-linear dynamic systems, the description of actors themselves become important, as small changes in input become large changes in output (Grimm et al. 2005). These descriptions can be subdivided into understanding the means of describing population demographics and behavioural typologies.

The demographics of an agent population can be thought of as the set of characteristics that end up influencing the expression of certain behaviours. ABMs support the instantiation of a diverse agent population, as opposed to the normative population of purely mathematical
Agent behaviour represents the ways an agent behaves towards a stimulus; the types of actions and interactions that demographics can ultimately express into. In BPS actions have been limited to adaptive and non-adaptive methods, where adaptive behaviours being those that change the state of a building system, in order to alter the conditioning of a space, while non-adaptive tends to refer to the use of other equipment (i.e., computers) (Deru, 2016). While this simplifies the interaction significantly, there have been more humanistic attempts to construct occupant typologies. BPS has focused these clusters on occupant opinions about how energy is consumed (Hoes et al. 2009). This method has been applied to the building scale as a means of simulating both the interaction with equipment and strategies for lowering consumption (Azar et al. 2012; Azar and Menassa 2010). Azar’s method breaks occupants down into only a small number of possibly categories, refinement towards more fit to purpose modelling techniques (Gaetani, Hoes, and Hensen 2016) and applied at the urban scale (Kontar and Rakha. 2018; Rakha, Rose, and Reinhart 2014). Clustering in effect sets the ground by grouping agents into a smaller number of representative types.

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These descriptions are data intensive and within the literature there remains concern as to how to acquire these data (Jia, Srinivasan, and Raheem 2017). While methods, such as surveys and direct observation continue to be popular methods (Hong, D’Oca, Turner, et al. 2015; O’Brien and Cowie 2017), they do not scale. Urban and building scale agent based modelling has made use of cell phone data (Jiang, Ferreira, and Gonzalez 2016), wifi traffic (Depatla, Muralidharan, and Mostofi 2015; Sevtsuk et al. 2008), bluetooth (Tekler et al. 2020) and other IoT approaches in an attempt to overcome the issue of scale (Akkaya et al. 2015; Plageras et al. 2018).

No matter how scalable, data require an organizational schema to allow data to be used within any architecture. as Drivers, Needs, Actions, Systems (DNAS) (Hong, D’Oca, Taylor-Lange, et al. 2015) and initial research into the creation of semantic vocabularies for occupant behaviour (Salimi, Nik-Bakht, and Hammad 2019) provide exactly this type of organizational framework. While Salimi (2019) proposes a model that captures a more complex agent architecture, these remain focused on the relationship between agents and building equipment.

Recent literature in BPS relating to ABMs discusses a need to include aspects of the social sphere (Hong et al. 2018), where excluding from the broader agent architecture leads to agents that are not believable (Jia et al. 2018). The ways of describing agents within ABMs are limited partly due to the ways the outcomes are used, industry software (e.g., Energy Plus) only accept schedules as inputs for modelling causing all of the added nuisance to be removed.

**Discussion**

The models we construct are based on a view of the world built on the things we assume to be true (Tuftte, 2020). Focus has primarily been given to the representation of buildings as systems of physical systems. While physical systems are also poorly represented the wholesale exclusion of social factors has played a significant role in the performance gap described in Sun (2014). The review of ABM methods in BPS show as they relate to occupancy show that ABMs still rely on an epistemic context that understands buildings through their systems. Our knowledge about buildings extends well beyond what can be directly measured and is contained in a historical body of qualitative knowledge concerning unmeasurable subjective qualities of space.

**Considerations for Agent Based Modelling**

There is a discrete advantage when considering the built environment and a high-performance building agenda in the use of agents capable of responding intelligently to their environment. This method at the very least validates, if not closes, the well documented performance gap in BEM (Jia et al. 2017). BPS has made use of ABMs primarily to calibrate or enrich existing models with physical systems, such as blinds and lighting systems (Chang and Hong 2013). Models are primarily generated.
to calibrate or enrich occupancy schedules for use with Energy Plus and other zonal energy modelling platforms. BEM applications have little to no room within the simulation environment, limiting the expression of agents and the potentials of ABM. Emergence is hamstrung in BPS by one of two extant issues. Either, the unit of analysis is simply too large, for example Nägeli et al. (2020) in which the agent is a whole building, or the agent’s motivation framework is too mechanistic to allow for emergence to take place at all, as in the case of models pertaining only to the operation of equipment. Both issues can be tied back to the reliance on enriching occupancy schedules used in zonal thermal modelling tools and the limited role that these have for occupants in the first place, giving them only qualities that relate to internal loads, equipment and lighting usage. There is a need for tools that take advantage of advances in software design and hardware architecture to move past the limits of Energy Plus and others and their reductive ontologies. In BPS the two most pressing considerations are the means of representing agents themselves and their social, material, and physical contexts. The other is the amount of data necessary to compile these representations.

Considering representation occupants, and by extension agents within a simulation or energy model, exist within an energy culture, the set of material conditions, practices and psychosocial norms that drive overall energy consumption behaviours (Stephenson et al., 2010). Representational frameworks for ABMs currently focus heavily on material conditions, the interaction with mechanical systems, see for example Azar and Lin (2017). The human sciences offer representational architectures that allow for the expressing of a wider array of elements relating to norms, social practices, regulation, and other elements of social behaviour not captured, or that due to the limitations of software cannot be expressed. For example, the BDI architecture captures more fully the way internal beliefs both specific to that agent and shared among agents, due to for example a regulatory context, influence both desire and the process of planning at an individual level.

The challenge of gathering data remains real, a shift in interest towards and the maturing of the internet of things (IoT) and smart devices present the opportunity to overcome the identified hurdle. This opens the possibility of data driven agent models. IOT represents an enormous potential for methods of data augmentation, from other fields, that are not being pursued. For example, the ability to use captured data in meta-models allows for the creation of projective proxy populations using machine learning methods such as random forests (Edali and Yücel 2019). This kind of data augmentation expands the possibility of representations to those that can exist, but may not have been encountered, or directly observed this critical for a diverse range of behavioural and demographic representations. Occupancy schedules, especially those built using transit demand surveys, are prone to bias that causes middle class professional labour to be disproportionately represented. The ability to use data to assemble and simulate the behaviour of a more diverse range of occupants will continue to prove out the role that people play in the performance gap between predicted and real use, as demonstrated by Jia (2017).

Software environments represent a significant hurdle that the reviewed literature indicates is an immediate issue facing wider use of ABMs in BPS; stagnation. While this can be explained by the afore-mentioned issue with software platforms the more pressing is the need for a unifying abstract definition of what is an agent and the role of the agent within a built environment. Tools that make use of ABMs to aid the design process ought to be exploratory and have models to support a “what if” way of thinking. This kind of thinking can allow the simulation to evolve with the model as different assumptions and configurations are tried, as opposed to being locked into late-stage validation of pre-existing assumptions.

Model Architectures for BPS Use Cases

When choosing to use ABMs the selection of the agent architecture is critical. Figure 1 provides a breakdown of major agent architectural frameworks that have been used in BPS. As can be seen there is no single architecture that can completely encapsulate an agent. Therefore, it is important to decide on what the purpose of the simulation is. Below are three common BPS use cases

1. HVAC System Sizing and Optimization

Agents in this use case move between spaces, have reasons to move between spaces, and these volumes need to remain comfortable. To get accurate sizing the analyst needs information about when and in which zones agents cluster to optimize HVAC supply. In this use case an agent architecture would be able to explain both physiology and agent cognition, in order to explain motivations at the level of an individual agent. In this case a cognitive agent model would be best fit.

2. Energy Use Intensity Estimation for Compliance

Cities are passing and enforcing a new generation of policies around building energy use (Belussi, 2019). Part of this will involve showing that a building ought to meet certain usage criteria. Agents in this case could be used to enrich the program schedule for a building based on a more diverse range of occupants with labour profiles, demands on time (i.e., single parents) and other factors that would influence when an agent was present and influencing the internal loads. In this use case demography and social dynamics are more critical than other factors, making BDI agents a fit to purpose.

3. Urban Resource Flows and Life Cycle Assessment

The purpose of this use case is to analyse how energy and resources are consumed over the life of a project. For instance, current methods do not effectively capture transportation energy and ABMs can capture information about mode split and destination choices. Agents would need to capture rational choices about traveling, a process that is well documented and driven by utility maximization (Traine, 2009), making rational agents, such as those demonstrated in Azar (2012) most suitable.
Conclusion

The literature review describes an array of available agent architectures that can be accessed, both from the work done within BPS and from the human sciences. Enriching models with sociological data can only serve to close the performance gap further and open behaviour design as an avenue for performance intervention. Shortcomings of ABMs and the assumptions they inherit as they are currently applied will likely continue to hamper application. Overcoming limitations begins from identifying a framework that can build off what the human sciences have learned about how to not just simulate people but understand the interactions of people with their social and physical environments.

Limitations and Future Work

There are two major limitations to wider scale application of ABMs. The first is the lack of a metadata schema that captures the rich nature of sociometric data. Second, is that there is no meaningful interface for the outputs of ABMs in current simulation platforms such as Energy Plus, where the representation of an agent is an occupancy schedule. While listed as an ABMs limitation, it is rather a limitation of the simulation engines themselves.

Future work focuses on a metadata schema to describe the ways people interact with their environment and the development of an ontological definition to describe the relationship of occupants with buildings that is extensible and will serve as the backbone of a flexible agent-based occupancy architecture for simulation.

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*Figure 1: Matrix of Agent Architectures*