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Architectural AI

Urban Artificial Intelligence in Architecture and Design

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Abstract

This chapter investigates the impact of artificial intelligence on contemporary cities through the lens of architectural and urban design. It explores design computing approaches where Artificial Intelligence (AI), Machine Learning (ML) and, generative approaches to urban design are employed to manage and create spatial configurations. Architectural AI hinges on the ideas of *digital demiurge* and *black box:* two intentionally polarised paradigms that underpin the idea of agency in the design process. The chapter explores the extent to which designers (or machines) are in control of the design process and final outcomes. This work provides examples of how the use of generative and intelligent systems is changing the way design is thought and produced. Conclusions suggest that the relationship that designers currently have with computers — and their agency over the production of urban space — is amorphous and non-hierarchical. This relationship is based on a profound collaborative human-machine paradigm and constant feedback loop between designers and AI, to the point that a design project could now be considered a truly collective oeuvre.

1 Introduction

This chapter investigates the impact of artificial intelligence on contemporary cities through the lens of architectural and urban design. It explores design computing approaches where computers characterise the production and management of design. These include Artificial Intelligence (AI), Machine Learning (ML) as a subset of AI and, in general terms, generative approaches to urban design where AI components are employed to create spatial configurations. We look at these systems as invisible forces that have significant consequences for both the built environment and people living in cities, providing examples and considerations of how intelligent systems and designers are reshaping cities today through a new form of agency. We present two intentionally polarised paradigms that underpin the idea of agency in the design process and the extent to which designers (or machines) are in control of the design process and final outcomes. These are the *digital demiurge*, where designers have full control of their project and, contra, the *black box*, where AI determines the final design outcome in an opaque and often inscrutable way.

The former position (*digital demiurge*) suggests that designers oversee the entire project from conception to construction. This may happen directly through traditional Computer-Aided Design/Computer-Aided Manufacturing (CAD/CAM) tools or indirectly when designers build their own automated design tools and decide the rules that AI will follow (although they may defer some decisions to an AI). The latter viewpoint (*black box*) suggests that designers may lose control of some part of the design, especially when complex AI models are used, or when the design process hinges on "closed" software packages, like proprietary Application Programming Interface (APIs), libraries etc.

The second section describes the P vs. NP problem to frame the deterministic versus non-deterministic nature of design within the context of human-made design and artificial intelligence. It explores the tension between the two paradigms through a theoretical framework meant to clarify how design agency moves across the two extreme positions of the digital demiurge and the black box. The third section describes practical design approaches to architecture, urban design, urban analytics and space-making in order to provide real-life examples of the complex designer/machine relationships and the author's agency in the era of urban AI (cf. Carpo, 2011). The conclusion elaborates on the importance of looking at the gradient between the *digital demiurge* and *black box* positions with nuance, and proposes a hybrid model of control and authorship between machines and humans, algorithms and designers.

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2 Coordinates

Artificial intelligence and machine learning methods are being increasingly used by designers and planners as a powerful tool to analyse, manage and design cities. Designers have engaged with digital technologies and computational methods for a long time, as the pioneering work of John Gero, George Stiny, Lionel March, William J. Mitchell, and Rivka Oxman, exemplifies. However, as artificial intelligence becomes increasingly present in a number of urban processes and systems and, more importantly, available to non-experts, its impact on the design of cities grows exponentially. Many authors have been exploring the importance of AI for urban development and planning, highlighting potentials and possible drawbacks (Batty, 2018; Barns, 2021; Cugurullo, 2020, 2021).

The relationship between designer and machine can be characterised by two extreme positions that hinge on the role of the designer within the automated (design) process. One position sees the designer as a central figure with complete control of the process, while the machine is considered primarily as a powerful yet passive tool. In the other, machine can be understood as an autonomous agent that takes a substantial role in the design process where, due to the complexity of the operations involved, computers have a higher degree of autonomy in decision making.

Such polarised understanding of *designers VS machines* is not a novel idea in design. Following a cultural trajectory akin to that explored by Eco (1954) in "Apocalypse Postponed", Bottazzi (2018:vii) eloquently illustrates the dichotomy between "detractors and devotees" – which in Eco's book were referred to as "Apocalyptic and Integrated Intellectuals" respectively – with regards to the adoption of digital technologies in design. "The former group stubbornly resists acknowledging that digital tools can be used generatively and therefore struggle to grasp the wider, often not even spatial, issues at stake when designing with computers. [...] The latter group […] attributes to computers such degree of novelty and internal coherence to self-validate any outcome" (Bottazzi, 2018:vii).

The following section delves into these two positions from an architectural design viewpoint and discusses the idea of the designer as a creator in full control of the creative process, which we name *digital demiurge* in reference to Plato's notion of an omnipotent, artisan-like creator. We position this concept in contrast to the notion of *black box*, where the machine produces its design outputs in inscrutable ways.

2.1 Digital Demiurge and the black box

[**Demiurge**] Within the context of computational design, AI can significantly extend designers' possibilities. With a fraction of the effort once needed to elaborate a single drawing, computation enables designers to produce accurate urban models, with greater precision than ever before. Similarly, with AI applications, one designer alone can do the work of ten (Maine 2020), handling a level of complexity unmanageable by humans. With the aid of computational toolsets (including data analysis, algorithms, and modelling), designers can create and manage complex projects in an effective and productive manner, limited only by computational capacity and speed. In the notational space of their design software (a two- or three-dimensional environment) and with the ability to manipulate code, designers have a great creative capacity and can generate objects and spatial configurations regardless of their complexity, thus becoming *demiurges* that shape and manipulate the digital world.

This idea of the architect as a creative mind with great power seems to fit what, since the Renaissance, has been known as the *authorial paradigm,* according to which, the person who retains the credit of the creative act is considered to be the *author*. Arguably, the one who produces the algorithms and then assembles and adapts them to achieve a desired (design) goal should be considered the author of the design. However, the notion of automation (an inherent part of computational approaches) implies a certain degree of collaboration (Carpo, 2017). Algorithms are produced and distributed among designers who can use, manipulate and adapt them, in relation to specific design problems. Within this open and shared domain, designers are responsible for the systematic combination of different elements of their projects. In this scenario, designers allow some agency to algorithms, while remaining in an overall position of control. But what happens when the complexity of algorithms increases to a point where designers lose overview of the design process? In this scenario, agency gravitates towards computers, thereby resulting in what is usually referred to as a *black box* situation.

[**Black Box**] With recent advancements in Neural Networks (NNs) research (see Chaillou 2019; Nauata 2021; Huang and Zheng 2018), a design solution may depend on several variables, including the type of neural network (a complex system of nodes and links through which messages are propagated by AI), its architecture (the structure of the network), the type and quality of input data, the type of learning and the number of iterations used in the training. This complexity makes the design outcome extremely hard for humans to predict and manage. Designers using computational methods are responsible for the selection and preparation of input data and are in charge of evaluating the results and outcomes. However, they have a limited understanding of the inner mechanisms of artificial intelligent systems. Designers need to trust the systems they are using to guide their design without necessarily having a deep understanding of how they work. Designers using algorithms are delegating their agency to systems that are hard if not impossible to comprehend; that is to say, they are *pushing a design through a black box.*

We borrow the definition of black box in design from Ozturk (2020: 3): "*as a device, system, or object evaluated by an input and output that does not contain any internal knowledge.*" This approach is characterised by a lack of transparency in the process where designers need to use their intuition to navigate the system (Ozturk 2020). We can trace the origin of the term *black box* back to 1970 when John Christopher Jones in his seminal book on design methods, explained that "*the* *most valuable part of the design process is that which goes inside the designer's head and partially out of reach of his conscious control* [...] *The blackbox view of designing* [suggests that] *the human designer is capable of outputs in which he has confidence, and which often succeed, without his being able to say how these outputs were obtained*" (Jones 1970:46).

More specifically, there are two levels of trust in an autonomous system, or degree of superficial understanding in the black box phenomenon. The first is related to designers who may not necessarily have the skills or theoretical knowledge to master algorithmic models, especially in ML and AI. This problem is somehow compounded by the proliferation of ready-made AI tools, libraries and software packages that make it possible for anyone with basic/medium (design) software skills to use AI applications (cf. Carta 2020). This phenomenon is even more evident when designers use proprietary software or libraries where source codes are not publicly available and therefore it is difficult to have a deep understanding of the mechanisms underpinning those programmes.

The second cause of superficial understanding (and thus control) in autonomous systems is related to the mechanics of AI and neural networks. This factor has to do with the complexity that characterises neural networks (NNs). In essence, a NN works through a sequence of nodes and links organised in levels (which are called layers or perceptrons). Data (like an image of a cat, for example) passes through many different layers to be classified. This means that a category (or class) is suggested by the neural network as an output. The network provides a suggestion for the picture used as the input (for example, "yes, it is a picture of a cat", or "no, this is not a cat"). As data passes through each layer, each piece of information is multiplied and added through a system of nodes (through layers) where complexity increases exponentially. Very soon the manipulation of information becomes too complex for the human brain to grasp. We are able to control the input of a NN and evaluate the accuracy of outputs (the *before* and *after* the computation), but the complexity that characterises the *in-between* layers is way beyond human reach.

<Figure 1 here>

Figure 1. This figure shows a simple neural network used to classify pictures into cats and no-cats. Photographs are fed into the NN as inputs and a binary decision (cat/no-cat) is produced as an outcome. Source: authors.

This critical aspect is evident in most machine training experiments in architectural design where the large amount of data needed for training is obtained from generic datasets such as Lianjia.com, SUNCG, LIFULL HOME, Archimaps or DeZeen. Training is one of the first stages in setting up a neural network, where humans provide a large number of correct examples ("this is a cat" and "this is not a cat") to the network which, in turn, "learns" to classify images. Even if, hypothetically, the black box could be opened and potentially even fully understood by designers, these operations may be simply uneconomical. Given the often frantic pace of work in architectural practices, urban designers and architects have little time or will to open the box and study it. This can lead to what can be termed a 'pragmatic' black box where designers employ AI instruments or packages without questioning their functioning as long as they are useful. In this case, agency shifts from the designer to an unquestioned automated system.

With the emergence of more sophisticated and autonomous design tools, the designer-machine relation becomes increasingly complex as computational methods become more elaborated and precise and more powerful tools are developed. Our analysis can help understand these changes through a theoretical lens borrowed from the domain of computer science: the deterministic versus nondeterministic approach in a P versus NP problem which we elucidate in the next section. We propose the deterministic (P) in contrast to the non-deterministic (NP) positions as a proxy to analyse the digital demiurge versus black box approaches and clarify the nuanced design agency within Architectural AIs.

2.2 P Versus NP problem

In computer science, *P* stands for polynomial time, while *NP* for nondeterministic polynomial time. The two terms refer to the time an algorithm takes to solve a given problem. There are problems that can be solved in a P time (more precisely, they belong to a P complexity class), which means that an algorithm can find the solution for the problem in an efficient and relatively fast way. Conversely, NP problems include those cases where an algorithm can find the solution, yet in a very long time, for example in exponential time (as opposed to polynomial time). However, the solution to such NP problems can be easily verified. This means that, once one can see the solution, it is relatively easy to verify its correctness. To ascertain, however, whether a problem that is quickly solvable (i.e. solvable in polynomial time) is also quickly verifiable is not banal, to the point that the question of whether P=NP or P≠NP is considered one of the most challenging and important mathematical problems of the millennium and is listed as one of the six unsolved mathematical problems of the Clay Institute (Clay Mathematics Institute 2022).

Within the design domain, NP problems correspond to design approaches where architects do not explore all possible options in order to find a solution, relying instead on intuition, experience and subjectivity. Once a possible solution is drawn, designers can easily and quickly verify whether it works or not. Note that the N in the acronym NP stands for "nondeterministic", indicating that the algorithm (or the designer) does not follow a particular rule in guessing the solution (Peres and Castelli 2021). We are suggesting here that both the designer and the algorithmic process that they develop have agency over the resolution of a design problem. The NP approach (guessing and quickly verifying the efficacy of the solution) is countered by the P model, whereby the designer follows an established set of rules. An example of a P problem in architecture may be about finding the best angle for a facade panel to maximise solar gain and avoid overheating at the same time, so the building maintains a good balance between natural light quality and energy performance. Such a problem is easily solvable using computational power where computers can calculate all possible solutions providing numerical values (e.g. energy performance, angles of each panel, etc.) to support the final choice. Conversely, an NP problem could be about determining whether or not a particular museum building shape will be appreciated by visitors. This is a problem that a computer is not able to resolve easily as it involves questions that are hard to encode in an algorithmic logic. However, any experienced architect would immediately be able to ascertain whether the suggested shape will work or not, simply by looking at it. This is when human experience and intuition come into play.

The difference between the two models underpins two different approaches to computation. The NP problem follows a *gut-feeling* approach (cf. Dawson 2015), guessing the design solution on the basis of instinct, experience and perception (within an NP class), whilst the P problem usually follows an established method or model (or series of rules) to determine the solution (P class).

The relevance of this paradigm is crucial. In the attempt of regulating automation in design and human-machine co-design, architects have developed a number of approaches which include shape grammars (Mitchell 1990; Çağdaş 1996; Lee, Ostwald and Gu 2021) and self-organising floor plans (Carta 2020) among others. Overall, as Derix (2014) notes, there are two main approaches to automation in design. One is pursued by John Frazer and Paul Coates from the 1960s onwards where the focus is on self-organising methods, autonomy of space and the translation of architectural skills and knowledge into computable techniques (Derix 2014). The second focuses on the search for objectivity and extreme rationalisation in the design process, where all nuances and complexities of human behaviours are reduced to computable and standardised factors (Derix 2014). Interestingly, the work of Frazer and Coates was underpinned by a heuristic approach, where generative design approaches were developed to systematically and intelligently reproduce the architect's knowledge and skills. Derix suggests that this latter approach was a sort of response to Organic architects (like Hans Scharoun and Rudolf Steiner, for instance) to systematise an empirical approach to space in architecture (Derix 2014:17).

The framework N-NP problem and deterministic versus non-deterministic approaches to design problems are helpful to understand the two positions that architects have with regard to algorithms. From this perspective, architectural design can be seen as a practice ranging from intuition to rule-based models. From a design perspective, this idea can be extended to both digital and physical relationships. There is no fixed hierarchy among the designers and AIs: individuals do not entirely control software, while, in turn, people are not (entirely) controlled by software. The same applies to the built environment, which is not entirely controlled by individuals or software and does not always or entirely determine designers' choices or how software adapts to the designed environment. In this perspective, the boundaries between the author and their instruments begin to fade.

One of the effects (or by-products) of the co-constitutive relationship between designer and software is *emergence*. The notion of emergence can be understood as "*collective phenomena or behaviors in complex adaptive systems that are not present in their individual parts*" (Pines 2014) and is related to a large body of studies, including the work of Holland (2000), Johnson (2002), and Watts (2000), to name but a few. In spatial and urban terms, there are key approaches that are used by designers to produce and manage emergent properties in the practice of space production. Examples include Procedural Content Generation (PCG; cf. Salge et al. 2018) where well-established techniques and algorithms used in computer graphics, video production and visual effects are applied to the generation of contents (architectural elements) in an urban environment (cf. Kelly and McCabe 2006 for an overview of most used methods). Such approaches may include the generation of spatial elements through well-known mathematical structures, including fractals (Mandelbrot and Frame 1987; Barnsley 2014), cellular automata (Wolfram 1983), and the production of voxels (e.g. Xiao et al. 2020) and maxels (Bottazzi 2018:177).

If the idea of N-NP problem helps to frame the designer-algorithms relationship in terms of deterministic versus non-deterministic approaches, the notion of emergence can be used to explain the dynamics that underpin those approaches. The N-NP problem explains how and why architects use algorithms in their design: how they solve design challenges by means of rule-based models or heuristics, and the extent to which designers trust algorithms and rules to resolve parts of the design, thus devolving part of their agency. In turn, the notion of emergence is helpful to see how such devolution is often neither linear nor hierarchical, but in a state of continuous adaptation, a condition that we will explore empirically in the next section.

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3. Autonomy at work: case studies

To clarify how algorithmic processes and AI work within computational design and how they have direct and indirect implications for the physical elements of the city, we analyse two case studies. First, we will discuss KPF Architects' One Vanderbilt in New York, NY (KPFui 2018) where a number of algorithmic models (including multi-objective optimization) have been used to determine the Floor Area Ratio (FAR), orientation, pedestrian flow and overall shape of the building and annexed public spaces. Additionally, we will examine the work of Carta et al. (2022) where Convolutional Neural Networks (CNNs) were used to understand and predict the spatial configurations that characterise urban areas in resilient communities.

The projects were selected to provide examples of how AI is currently applied in the Architecture Engineering and Construction (AEC) industry at two different scales: i) multi-purpose high-rise and complex buildings (One Vanderbilt in New York) which, due to their high complexity, influence the infrastructure, mobility and overall social use of the urban area surrounding the building; and ii) neighbourhood scale (AI for resilient communities), where AI methods are used to explore the social use of space in urban communities. The selected projects represent two of the main AI-mediated approaches to architecture and urban design: design optimization (the systematic change of a number of design variables to obtain a desired solution measured in terms of performance) and design inference, where a mathematical model is applied to discover new urban aspects (in this case, urban resilience).

In analysing and discussing these projects, we focus on two main aspects: i) the algorithmic strategies and the use of AI-based models to inform the design process in general, as well as the generation of architectural forms and spatial configuration specifically; and ii) the designer/computer relation along the entire design process. Furthermore, we intentionally emphasise the quantitative nature of some architectural processes over the appreciation of qualitative aspects. Most of the design methods included in these projects work under the assumption that aspects of the built environment can be accurately measured and quantified. As such, they can then be optimised against measurable targets (for example the amount of energy used by a building, the length of walking paths for pedestrians, etc.). As these projects are instrumental to illustrate how AI is currently used in urban design, we admittedly exclude those aspects of the built environment that are inherently qualitative and relate to the subjectivity, indeterminacy and uncertainties that (also) characterise our cities (Sennett 2012).

3.1 One Vanderbilt in New York

[**Brief description**] One Vanderbilt is a complex 162,600 square metre multi-programme building in Midtown Manhattan designed by global architecture firm KPF and completed in 2020. The project includes spaces for civic and cultural activities, mixed-use programmes, office spaces, transportation sections and retail areas strongly connected to the existing city fabric and infrastructure. The building is directly connected to Grand Central Terminal. The 427-metre-high main tower is the combination of four interlocked and tapering sections that have been shaped to respond to a number of criteria, including a formal and visual relationship with the nearby Chrysler Building and adjacent Grand Central. Corners of the main volumes have been cut to maximise the view from the street and to emphasise key pedestrians' perspectives.

<Figure 2 here>

Figure 2. Skyline of Manhattan with One Vanderbilt (the tallest building on the left) shown in its urban context. Raimund Koch / Courtesy of Kohn Pedersen Fox Associates.

[AI methods] As a part of this project, the computational section of KPF, KPFui (Urban Interface) developed an analytical tool that, through simulations, helped designers to encode several inputs and criteria from different stakeholders into the design process. This method involved a multi-objective optimisation approach where several objectives are included in the computation. Such objectives may be articulated in terms of minimisation or maximisation of performance value of the building; for example, minimisation of solar heating or maximisation of pedestrian flow. In particular, the designers focused on the maximisation and quality of sky exposure, which can be defined as the quantity of sky visible by users of the building (both inside and outside of the building envelope). The amount of sky that people can see is a component of a more general measure of ambient daylight access (KPF 2021), which contributes to the overall environmental quality of the project. Once the parameters for optimisation had been determined, the designers employed an evolutionary solver based on a genetic algorithm and a simulated annealing algorithm

(Rutten 2013:132). Both algorithms are based on real-life experience, one drawing from physics and metallurgy and the other one from biology and genetics (Rutten 2013:135). Evolutionary solvers are a powerful method to determine the best solution for a given problem. By best solution, we intend the (design) solution that is the closest to a pre-set value (a minimum or maximum value, for example). Possible solutions are generated by altering a set of parameters within given ranges and then evaluated using a fitness function, i.e. a mathematical function that compares solutions to a desired value and evaluates how close each design solution is to the optimum score.

<Figure 3 here>

Figure 4. Interface used by the architects to visualise the results of the genetic algorithm (right-hand), its performance (centre) and the final building shape resulting from the computation (left). Source: https://ui.kpf.com/one-vanderbilt

Although an evolutionary solver is not strictly categorised as artificial intelligence since it is not able to learn and make decisions independently, it is a good example of how computational methods are applied to help designers with complex design tasks, identifying optimised solutions and devising better strategies to tackle complicated design challenges.

[**Relation AI/designer**] The formal research which led to the final form of One Vanderbilt was made possible by advanced computational tools that allowed for the use and manipulation of complex algorithms. The designers are empowered by the machine, and in near real time can explore infinite variations and weigh their impact on an array of significant metrics. They can do that after the design of the optimisation criteria and the implementation in the form of a machine-readable system is decided at the start of the project. During the form-finding operation, agency is shared by the designer (that inputs and tests the machine) and computers (that retrieve the desired inputs).

The method developed by KPF for this project supported the designers to "*reconcile competing objectives and facilitate the design*" of the building (KPF 2021). With this project, designers relied on a quantitative and analytical approach to find the best solution for complex design problems, for example reducing the portion of sky that the new building would block, optimising pedestrian circulation, maximising street views and perspectives. Moreover, the KPFui team devised a robust method that allowed them to positively interact with the stakeholders involved in the design and approval process. "*Once the design for One Vanderbilt was made public, it became especially important to communicate its impact to the community board and the Landmarks Preservation Committee. Our models and data analysis were key to facilitating the conversation and the review process*" (KPF 2021). It is worth noting that an evolutionary solver can perhaps illustrate more easily (compared to a traditional neural network approach) the extent to which designers have an active involvement in the human-machine collaboration within design. The parameters to be optimised (minimised or maximised) are decided by the designers in consultation with stakeholders, including representatives of local communities, regulators, and local governments. The fitness function (and therefore the desired values for each performative aspect of the project) is decided by designers on the basis of what is expected and needed for the building. The generative process which underpinned the evolutionary phase yielded multiple design solutions (options) which have been selected by the computer (through a function) which is instructed and monitored by the designers. In this example it is easy to see how the computer has been given clear tasks under close observation. This approach clearly illustrates a case of P class problems, where the domain of possible solutions can be easily and exhaustively computed by a machine through a finite number of logic steps. The designer instructs and oversees this process, expecting a defined output that will inform further design decisions.

3.2 AI for resilient communities

<Figure 4 here>

Figure 5. Example of satellite images used for the training of the ML model. The neural network has been trained to detect key elements in the images and classify them into pre-determined groups, including buildings, infrastructure and green areas. Source: authors.

[Brief description] Machine Learning (ML) methods have been extensively and successfully used to simulate new configurations and explore possible design solutions in cities (e.g. Steinfeld 2019; Wallish 2019; Del Campo et al. 2021). However, so far these methods have not largely been used as quantitative tools for urban analysis and assessment, especially in net-zero and resilience design. With this project (Carta et al. 2022), we started exploring a new method to generate a tool that can help designers, local governments and policymakers to automatically calculate the degree to which a specific neighbourhood is (and can be) resilient, on the basis of a given urban configuration.

[**AI methods**] The project explores the extent to which deep neural networks (specifically Convolutional Neural Networks) can help designers quantitatively assess the level of resilience of urban areas and suggest how to improve it. Working from the assumption that the behaviour of people in a neighbourhood is heavily influenced by the spatial configuration and architectural forms of that neighbourhood, we used a combination of AI methods (primarily based on object-detection) to assign to each given area a resilience score. We employed Convolutional Neural Networks (CNNs) to extract spatial features that characterise resilient areas. In very simple terms, a convolutional neural network is able to extract features from images with gradual levels of abstraction through filters. The first filters provide low levels of distinction; for example main lines and boundaries dividing areas with colours in stark contrast. After multiple iterations, the neural network gradually raises the level of abstraction to recognise medium-level features; for example, eyes and noses in human faces. Finally, the last set of filters are able to extract high-level features that imply a certain level of intelligibility such as facial expressions and emotions. Sequential levels of abstraction are generally referred to as layers and their depth determines the way in which the neural network learns.

In this project, we used a large set of satellite images to train the CNN to detect the presence of key urban typologies that have a high influence on resilience, including green and recreational areas, transportation buildings (e.g. train and bus stations), and key buildings like schools, museums and civic centres. Once trained, the model returns a resilience score for each urban area. We validated the model (via the method developed in Carta et al. 2021) using a linear equation that considers the distance of key typologies (schools, green areas, train stations, etc.) from the centre of the neighbourhood. We used a combination of data sources and software packages, including OpenStreetMap, QGIS, Rhinoceros Grasshopper, as shown in Figure 6.

<Figure 5 here>

Figure 6. Data points representing the georeferenced position of key urban elements (bus stops, schools, train stations, etc.) from OpenStreetMap (left) are computed into a linear equation that returns an overall value of resilience (right). Source: authors.

[**AI/designer Relation**] Experimentation with CNNs allows designers to partially open a very complex system that is otherwise considered as a black box. Feedback-loop mechanisms allowed us to adjust the way we trained them to the point that we could predict (to a certain extent) the behaviour of particular urban systems and produce a set of reliable analytics.

At the end of the process, our tool was able to recognise key elements in urban areas (for example, a primary school or a housing unit), establish the walkable distance between the centre of the area and each building or green area, and return a general value of resilience for that area. As in the previous example, the agency over the design alternates between the designers and the algorithms used. We argue, therefore, that agency is in this case multileveled. First, there exists an element of design in both the overall project (including the theoretical premises for such work) and the algorithms, APIs and libraries employed. There are multiple designers with different levels of trust. For example, we, as architects and urban designers, used software libraries which consist of code and routines written by other designers for different purposes. In particular, we used a detection algorithm called YOLOv5 (You Only Look Once), developed primarily for object detection in videos and with moving objects. We adapted the library running YOLOv5 for our own purposes. We therefore asynchronously collaborated with other designers (of algorithms and software packages).

Second, we trusted the libraries and APIs we used in this project to run calculations for us, specifically the object detection and the classification of key urban elements. As designers, we made choices and selections during this process, sending partial results back to our model for refinements. This approach creates an iterative process where designers and machines cooperate. On a deeper level, we should mention that the computations were run both locally (on our local computers) and remotely (using graphical processing units (GPUs) within the Google Colab environment). We also used a number of software frameworks (e.g. PyTorch) and parallel computing platforms (e.g. CUDA) as a part of our ML process.

Finally, since our model has been published as a web app, we have extended its agency so that other designers can use it from their own computer without our intervention. As our model has been completed, at least at a prototype stage, the ML process works automatically and without the control, input or supervision of the original designers. Users of the app will make their own use of the model, changing settings, areas and scale of the selected urban context.

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4. Conclusion: a different kind of agency

In the described case studies, we can see how AI can be employed as an integral part of the design process. Borrowing from algebraic concepts, Bernard Cache describes this process of parametrisation (notations) through the notion of *objectiles* (Cache 1999). The idea is depicted using the example of a single function (for example *f(x) = y)* that can contain infinite possible formal outcomes depending on the parameters chosen (Cache 1999). The idea of an *objectile* is helpful to describe an open system: a model where a flexible basic structure is coupled with variables that can be filled with different values depending on the design strategy. This notion is purposely generic, for it can be applied to many types of work. When an *objectile* is applied to a concrete design project, this becomes a *projectile* (Cache 1999). Within the domain of digital and computational architecture, a projectile is expressed in the form of a series of algorithms created and combined by designers to address a specific design challenge. A case in point is One Vanderbilt where the project can be seen as the result of the collaboration between designers and machines. The building, in its infinite variations, remains under the control of the designers as projectile. The designers, having evaluated the complex results from the computation, have the ability to select the most suitable options for a given project. In Resilient Communities, several different *objectiles* were combined and applied, through reiterated tests and operations until the results were deemed satisfactory against a predetermined set of design objectives. Here the process is more fluid, and changes at every iteration, combining parts developed by different designers and machines. While in One Vanderbilt the design task consists in *finding* the best possible solution to a given design problem (projectile), the main task in Resilient Communities is to exist as an objectile, embodying different possible abstract configurations at once. In this case, architects and planners are still responsible for devising the design strategy and combining the different parts of the process together. However, to obtain more complex and performative formal results, designers must test their ideal spatial configuration against many AI-generated options. In such processes, the design agency moves from the (human) designer who is in full control of certain phases to algorithmic processes where humans devolve their control to automated routines and complex calculations, with a certain degree of serendipity. This complex relationship between human and AI is summarised in Figure 7.

<Figure 6 here>

Figure 7. Co-creation scheme of design agency in architectural artificial intelligence (AAI) where architectural design is the product of the interaction of the designer with AAIs. This diagram illustrates how the process starts with "the designer" and "other designers and software developers" as the two main input of the architectural artificial intelligence. The input of the designer translates into data curation and the supervision of the entire process which, in turn, provides certain feedback to the designer who can then consider it for the next cycle in the process. This internal feedback loop of designer-algorithmic system is coupled with the input from other designers and developers producing the AAI as results that eventually yields the final design as the ultimate outcome. Source: authors.

While it is certainly true that AI has the potential to produce a paradigm shift in design practices, this does not mean that AI tools will necessarily reduce the need for designers or even free them from the burden of responsible work. Moreover, we do not expect AI to foster an inscrutable production of space without human supervision, at least in the near future. While designers are constantly looking for ways to devote as much time as possible to the design activity in order to produce better designs (Fairs 2021), they are also called to change their way of thinking and approaching design problems, by studying, for example, algorithms and data structures to be able to "justify every single design decision your computer has made on your behalf" (Rutten 2021:132).

Once developed, architectural AI tools must still be managed, questioned and combined with the work of other designers. A fundamental aspect of this collaborative paradigm is that the diversity of approaches, solutions, and the 'cultural milieu' of architectural and urban design remain preserved, as well as empowered, by AI tools. Rather than fitting already existing paradigms (and thus becoming a mannerism), architectural AIs can potentially produce their own expressions in new design schemes and discoveries. As illustrated by a recent exchange between Thom Maine (Morphosis) and Wolf Prix (Coop Himmelb(l)au), two of the most prominent architects working in the digital architecture domain, the designs produced by AI are “more engaging, compelling, useful than the one I did that was manipulated through my own single instinct” (Maine 2020:14:46).

What we define as Architectural Artificial Intelligence (AAI) is currently at the centre of a fast-paced experimentation among design practices. In this sense, AAI is a relatively recent field of exploration in design studies which, as a consequence of its application of AI to design, heavily connects the traditionally complex fields of architectural industry to computer science, formal methods, and to some extent neuroscience and ethics. All these interdisciplinary components converge into a complex human-AI relationship. The nature of this relation is constantly mutating. Architectural AIs, framed as *digital demiurges* or as *black boxes*, correspond to two polarised stances. We suggest that the relationship that designers have with computers and therefore their agency over the production of urban space is amorphous and non-hierarchical. Today, design automation entails a profound collaborative paradigm and constant feedback between designers and AI, to the point that a design project can be considered a collective oeuvre.

References

Barns, S. (2021). Out of the loop? On the radical and the routine in urban big data. *Urban Studies*, *58*(15), 3203-3210.

Barnsley, M. F. (2014). *Fractals everywhere*. Academic press.

Batty, M. (2018). Artificial intelligence and smart cities. *Environment and Planning B: Urban Analytics and City Science* (Vol. 45, pp. 3-6): SAGE Publications Sage UK: London, England.

Blau, J. R. (1976). Toward A Scientific Architecture by Yona Friedman. The MIT Press, Cambridge, Massachusetts, 1975. pp.169 (Translated by Cynthia Lang.). *International Journal of General System*, *3*(1), 68-70.

Cache, B. (1995). *Earth moves: the furnishing of territories*. MIT press.

Cache, B., & Girard, C. (1999). Objectile: The Pursuit of Philosophy by Other Means? In Stephen & P. (ed.) (Eds.), *Hypersurface Architecture II* (Vol. 69 (9/10), pp. p. 67).

Çağdaş, G. (1996). A shape grammar model for designing row-houses. *Design Studies*, *17*(1), 35-

51.

Carpo, M. (2011). *The alphabet and the algorithm*. MIT Press.

Carpo, M. (2017). *The second digital turn: design beyond intelligence*. MIT press.

Carta, S. (2019). *Big data, code and the discrete city: Shaping public realms*. Routledge.

Carta, S. (2020). Machine learning and computational design. *Ubiquity*, 1-10.

Carta, S. (2021). Self-Organizing Floor Plans. *Harvard Data Science Review HDSR*.

Carta, S., St Loe, S., Turchi, T., & Simon, J. (2020). Self-organising floor plans in care homes. *Sustainability*, *12*(11), 4393.

Carta, S., Turchi, T., & Pintacuda, L. (2022). Measuring Resilient Communities: an Analytical and Predictive Tool. In Jeroen van Ameijde, Nicole Gardner, Kyung Hoon Hyun, Dan Luo, Urvi Sheth (eds.), *POST-CARBON - Proceedings of the 27th CAADRIA Conference*, Sydney, 9-15 April 2022, pp. 615-624

Chaillou, S. (2019). AI Architecture Towards a New Approach (2019). *URL https://www. academia. edu/39599650/AI_Architecture_Towards_a_New_Approach*.

Cugurullo, F. (2020). Urban artificial intelligence: From automation to autonomy in the smart city. *Frontiers in Sustainable Cities*, *2*, 38.

Cugurullo, F. (2021). *Frankenstein Urbanism: Eco, Smart and Autonomous Cities, Artificial Intelligence and the End of the City*. Routledge.

Dawson, J. (2015). Building to sustain body and soul. *JBU Journal of Biourbanism*, Volume 01-02/2014-2015 p.49.

Del Campo, M., Carlson, A., & Manninger, S. (2021). Towards Hallucinating Machines-Designing with Computational Vision. *International Journal of Architectural Computing*, *19*(1), 88-103.

Derix, C. (2014). The Space of People in Computation. In Derix & Å. e. Christian and Izaki (Eds.), *Architectural Design* (Vol. 5, pp. 14-23). Wiley.

Durmus Ozturk, S. (2020). Rethinking the black box in architecture design studio. *SAGE Open*, *10*(2), 2158244020927408.

Fairs, M. (2021). Artificial intelligence "will empower designers" say Clippings co-founders. *DeZeen*. Available at: https://www.dezeen.com/2021/08/19/artificial-intelligence-empower-designers-clippings-co-founders/

Foth, M., Forlano, L., Satchell, C., & Gibbs, M. (2011). *From social butterfly to engaged citizen: Urban informatics, social media, ubiquitous computing, and mobile technology to support citizen engagement*. MIT Press.

Holland, J. H. (2000). *Emergence: From chaos to order*. OUP Oxford.

Huang, W., & Zheng, H. (2018). Architectural drawings recognition and generation through machine learning. *In Phillip Anzalone, Marcella Del Signore, Andrew John Wit (eds.) Proceedings of the 38th Annual Conference of the Association for Computer Aided Design in Architecture (ACADIA).* Universidad Iberoamericana, Mexico City.

Clay Mathematics Institute (2022. Millennium Problems). *Millennium Problems*. Clay Mathematics Institute. Available at https://www.claymath.org/millennium-problems.

Johnson, S. (2002). *Emergence: The connected lives of ants, brains, cities, and software*. Simon and Schuster.

Jones, J. C. (1970). *Design methods: seeds of human futures*. Wiley Interscience. *New York*.

Joyce, S. C., & Nazim, I. (2021). Limits to Applied ML in Planning and Architecture-Understanding and defining extents and capabilities. In Stojakovic, V and Tepavcevic, B (eds.), *Towards a new, configurable architecture - Proceedings of the 39th eCAADe Conference* - Volume 1, University of Novi Sad, Novi Sad, Serbia, 8-10 September 2021, pp. 243-252

Kelly, G., & McCabe, H. (2006). A survey of procedural techniques for city generation. *ITB Journal*, *14*(3), 342-351.

Kitchin, R. (2014). *The data revolution: Big data, open data, data infrastructures and their consequences*. Sage.

Kitchin, R., Lauriault, T. P., & McArdle, G. (2018). *Data and the City*. Routledge London.

KPF. (2021). *Case Study: One Vanderbilt. New York, NY.* Available at: https://ui.kpf.com/one-vanderbilt Last accessed 15 February 2022.

KPFui. (2018). *One-Vanderbilt*. https://www.kpf.com/projects/one-vanderbilt and https://ui.kpf.com/projects.

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. *Advances in neural information processing systems*, *25*.

Lee, J. H., Ostwald, M. J., & Gu, N. (2021). A statistical shape grammar approach to analysing and generating design instances of Murcutt's domestic architecture. *Environment and Planning B:*

Urban Analytics and City Science, *48*(4), 929-944.

Mackenzie, A. (2002). *Transductions: Bodies and machines at speed*. A&C Black.

Mandelbrot, B., & Frame, M. (1987). Fractals//Encyclopedia of Physical Science and Technology. *Academic Press, Inc., San Diego CA*, 579-593.

Marston, S. A., Jones III, J. P., & Woodward, K. (2005). Human geography without scale. *Transactions of the institute of British geographers*, *30*(4), 416-432.

Mayne, T., & Prix, W. (2020). *DigitalFUTURES: FROM DECON TO AI: AI and Architectural Practice.* https://www.youtube.com/watch?v=OlvYzmWuMsU Last accessed 25/04/2022., Youtube.

Mitchell, W. J. (1990). *The logic of architecture: Design, computation, and cognition*. MIT Press.

Nauata, N., Hosseini, S., Chang, K.-H., Chu, H., Cheng, C.-Y., & Furukawa, Y. (2021). House-GAN++: Generative Adversarial Layout Refinement Network towards Intelligent Computational Agent for Professional Architects. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition.

Negroponte, N. (1969). Toward a theory of architecture machines. *Journal of Architectural Education*, *23*(2), 9-12.

Oxman, R., & Gu, N. (2015). Theories and models of parametric design thinking. In Martens, B, Wurzer, G, Grasl T, Lorenz, WE and Schaffranek, R (eds.), *Real Time - Proceedings of the 33rd eCAADe Conference* - Volume 2, Vienna University of Technology, Vienna, Austria, 16-18 September 2015, pp. 477-482

Peres, F., & Castelli, M. (2021). Combinatorial optimization problems and metaheuristics: Review, challenges, design, and development. *Applied Sciences*, *11*(14), 6449.

Pines, D. (2014). Emergence: A unifying theme for 21st century science. Medium. Available at: https://medium.com/sfi-30-foundations-frontiers/emergence-a-unifying-theme-for-21st-century-science-4324ac0f951e

Rittel, H. W., & Webber, M. M. (1973). Dilemmas in a general theory of planning. *Policy sciences*, *4*(2), 155-169.

Rutten, D. (2013). Galapagos: On the logic and limitations of generic solvers. *Architectural Design*, *83*(2), 132-135.

Rutten, D. (2021). The inevitable and utter demise of the entire architectural profession.

https://discourse.mcneel.com/t/unpublished-opinion-piece/118250.

Salge, C., Green, M. C., Canaan, R., & Togelius, J. (2018). Generative design in minecraft (gdmc) settlement generation competition. Proceedings of the 13th International Conference on the Foundations of Digital Games.

Sennett, R. (2012). No one likes a city that's too smart. *The Guardian*.

Senseable City Lab. (2019). *AI Station. Senseable City Lab*. Available at: http://senseable.mit.edu/ai-station/app_wifi/ last accessed 14 February 2022.

Steinfeld, K. (2019). GAN Loci. 392-403. In *ACADIA 19: UBIQUITY AND AUTONOMY*. Proceedings of the 39th Annual Conference of the Association for Computer Aided Design in Architecture (ACADIA) ISBN 978-0-578-59179-7. The University of Texas at Austin School of Architecture, Austin, Texas 21-26 October, 2019. pp. 392-403

Wallish, S. (2019). Counterfeiting daily: An exploration of the use of generative adversarial neural networks in the architectural design process. Columbia University. https://open.library.ubc.ca/cIRcle/collections/graduateresearch/42591/items/1.0387289

Wang, Z., Liang, Q., Duarte, F., Zhang, F., Charron, L., Johnsen, L., Cai, B., Ratti, C. (2019). Quantifying legibility of indoor spaces using Deep Convolutional Neural Networks: Case studies in train stations. *Building and Environment*, *160*, 106099.

Watts, D. J. (2000). *Small worlds: The dynamics of networks between order and randomness*. Princeton University Press Princeton.

Wolfram, S. (1983). Cellular Automata, *Los Alamos Science*. *vol*, *9*, 2-21.

Xiao, K., Chen, C.-c., Guo, Z., Wang, X., & Yan, C. (2020). Research on Voxel-based Aggregation Design and its Fabrication. In D. Holzer, W. Nakapan, A. Globa, I. Koh (eds.), *RE: Anthropocene, Design in the Age of Humans - Proceedings of the 25th CAADRIA Conference* - Volume 1, Chulalongkorn University, Bangkok, Thailand, 5-6 August 2020, pp. 13-22