AI In+form: Intelligence and Aggregation for Solar Designs in the Built Environment

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Abstract. Designers are increasingly challenged by a constant change of context and the interaction of layers of data from a huge variety of sources, from natural-artificial to human-machine. This research aims at mapping the interrelations of energy problems, bio- and artificial intelligence, and human-machine interaction to reflect and rethink the future of solar design. This paper first discusses its theoretical approach that stands at the convergence of light-harvesting systems, their aggregation and intelligence. Afterwhich, this paper explores their translation into iterative processes between designer and artificial intelligences, which is defined as rule/agent-based and machine learning systems; in particular, the relationship between Cellular Automata, Genetic Algorithm, and Generative Adversarial Networks (GANs) is discussed. Finally, it introduces a design project - @R.E.Ar_ - showing the proposed combinatorial pipeline and some preliminary results.

Keywords: artificial intelligence; bio-inspired form-finding; solar design; Cellular Automata Aggregation; human-machine interaction

1 Introduction

'AI in+form' explores Artificial Intelligence (AI) informed design flows with a focus on solar designs, where form-finding is not taken simply as an optimal resultant shape, but information that informs energy circulation. Such information comprehends beyond a singular unit to the aggregation of units that operate in a strict relationship with an environment and available energy. The design process is facilitated by circular feedback between human and machine intelligence - AI in form informed by information.

Recent material advancements in thin-film smart materials (i.e. self-cleaning nano structures, electrical chromatic) that are flexible and lightweight, efficient under indoor lighting and low-voltage, customisable and economical (techniques like spin coating) offer designers inspiration to new solar design discourses (Macdonald, et al., 2019). In particular, carbon-based materials provide prospects in paralleling bio-mimicking generative designs with energy exchange mechanisms of organisms, spurring research that looks deeper into biological systems and their intelligence.

How can designers notate computationally, not just the complexity of the forms in light-harvesting organisms, but also their aggregation and distribution, taking solar data as sets of instructions for the design and arrangements of photovoltaic elements in the built environment?

2. Artificial Intelligence and Aggregation

Artificial intelligence, AI, is the scientific field that studies and attempts “to build intelligent entities” through virtual agents, which act “to achieve the best outcome or… the best expected outcome” of a given problem (Russell and Norvig, 2010). These problems are often associated with the automation of intellectual labour; however, they are not necessarily designed by mimicking what humans would do in the same scenario, and their development is done around the abilities to artificially reason over complex cases and learn from large datasets to produce specific results. This research is particularly interested in rule/agent-based and machine learning (ML) systems.

2.1. Rule/agent-based: Cellular Automata (CA)

Cellular Automata (CA) is a physical simulation system that uses an automaton developed by mathematical computational models running a limited set of simple rules inside a discrete environment (Von Neumann, 1966). Activating the discrete grid state from a simple on and off (0 to 1) in its basic form, a CA “seed” can produce an enormous set of results which are used to solve problems from biology, physics, structures, and urban studies as a datum of scales. CA's core elements are individualised and defined as ‘Neighbourhood’, ‘Discrete System’, ‘Abstraction’ and ‘Dynamism’ (Wolfram, 2002). Without which, one is not a proper CA System; still, logics of aggregations can be extrapolated from such systems, focusing on parts and combinations instead of relationships between different CA seeds in a growing collaborative process - a complex system in a discrete environment.

From the diversity of patterns that it's possible to create from CA as a simulation tool, all the richness of CA can be appreciated in terms of possible emergent patterns with changes in a few parameters in its configurations and rules, from where the possibles scenarios must be understood so as to implement these systems as the base of research. The combination of possible scenarios is a measure of entropy, tying information entropy with that of energy.

CA belongs to the Automata theory, a theoretical branch of computer science which has been developed and funded from the 20th century till our days, developing theoretical and physical machines, dealing with the logic of computation with respect to simple machines, referred to as automata, by which scientists can understand how the machines can compute functions and solve problems (Ulam, 1962). Automatons are abstract models of machines that perform computations on input by moving through a series of states or configurations. At each stage of the calculation, a transition function determines the next setup based on a finite portion of the present composition. As a result, once the computation reaches an equilibrium configuration, it accepts that input into a feedback loop. The most general and consequential automaton is the 'Turing (1936) machine'.

One of the essential features in CA is the concept related to the neighbourhood of each cell, with an assigned predefined state (state = 0) that a set of rules will change, being given a new state (state =1), emerging a new generation which functions can again reassign for specific purposes and scales of application. After this process, an "activated" neighbour emerged from the original discrete universe around the initial cell. The rules usually are running in a generative way (time), and, in the basic systems of this kind, it remains fixed; meanwhile, the code is running over this simulated universe. A cell's neighbourhood definition is determined by the local configuration of the discrete network in which the "seed" cell itself plus all the directly connected activated cells (Conway, 1971).

CA started as a discrete cellular system, composed as a finite set of elements, homogenous in its shapes, and individually isolated as units called cells. Simultaneously, this system works in a certain amount of time, generating discrete cycles and a finite set of states (Minsky, 1967). The idea of discretisation works into CA logic as a complexity abstraction engine operating by its own geometric simplicity, allowing each cell to evolve in each step, exchanging a limited set of information from the restricted neighbourhood (a local action) designed at the process beginning. Discrete at the end is the catalyst of complexity by simplicity.

Natural patterns are perfectly simulated with this complex system due to its results based on the interaction of simple growing rules in a strict relationship with an environment and the rational use of energy and matter in the process. Being the result, the best possible answer to the interaction of these elements in an n-dimensional space. Thus, such aggregation logic promotes options over optimal solutions in an ever changing dynamic process - Dynamism.

Working with aggregated geometries, adding features that can define a CA, it's possible to achieve a spectrum of outputs that inform the final result speculatively, opening possibilities of our designs to operate in a hybrid model, from seeds as agents with geometrical outputs as rules of aggregation. This facilitates the testing of alternative data inputs, such as solar radiation, that can dramatically improve the light-harvesting quality of the outcome, iterating possibilities in an evolutionary way and adding richness to the final designs.

2.2. Machine Learning (ML)

ML algorithms utilise learning strategies to evolve and achieve an objective, and are usually trained by being exposed to large amounts of data or scenarios that they can observe (collect information) and modify (act upon). These characteristics allow for these algorithms to uncover / discover patterns and predict future states, such as user preferences on the internet, or automate computational, cognitive or operational tasks, such as self-driving vehicles (Zuboff, 2019). While the fast paced development of the technology makes it hard to define what ML cannot achieve, it hints that the limitations are mostly defined by the currently available computer hardware; that said, the use of ML algorithms requires careful considerations to accompany it.

By learning from data or from crafted environments, ML carries the biases present in its development, rendering the process of collecting and selecting data for the algorithm to learn from one of the most important steps in the design of a ML algorithm. A poorly constructed dataset or environment can lead to the reinforcement of prejudices, unfit predictions and behaviours. However, this research chooses to take advantage of biases in our application of ML for the purpose of formulating human-machine interaction.

The intention is to use the data produced in the intuition-based and computationally intensive design process from rule/agent-based systems to create the training material that will assist the machine in learning the hidden patterns of this relationship and predict the results in a relatively instantaneous manner. More specifically, the algorithm should define a 3-dimensional shape in a given urban context, to the aggregation of architectural components, following a strategy that maximises the accumulated solar incidences on the surface of a form, seeking to maximise the capacity of building structures in producing energy via photovoltaic elements.

3. A Solar Design Research: @R.E.Ar_

The approach of this research emphasises options over optimal-solutions, channelling this to diversify solar designs that can be aggregated for diverse building topologies and user demands. Instead of generating one design to be used for every solar problem, this research focuses on ‘AI in+formed’ workflows, generating families of designs that are adaptive to each other, performing aggregation that aims at pertaining to a quartered law of nonlinear power scaling. With each discrete element to be fabricated in similar methods using the same mathematical conception. How to enable variational designs that win over diverse solar vectors in a complex environment through aggregation?

3.1. Combinatorial Pipeline

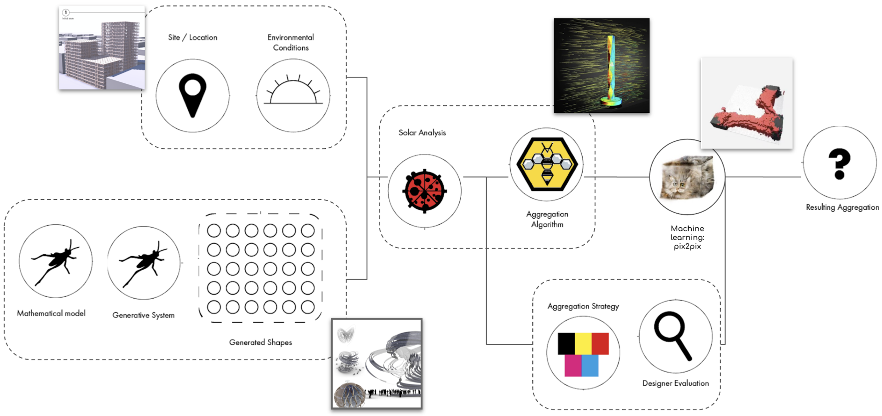

Figure 1. ‘AI in+form’ workshop by @r.e.ar (2021).*Combinatorial pipeline: rule/agent-based and ML system embedding designer intention.*

The combinatorial pipeline starts by creating the processes to be automated. The designer begins by defining a 3-dimensional continuous shape that is governed by a number of numerical parameters - creating a possibility space of the conceivable resulting shapes. Over this shape, a visual algorithm is applied resulting in an aggregation of cubic voxels (3-dimensional elements that represent a given position and volume in space, while also containing data). At this stage, a parametric structure is produced by the algorithm, following the intent of the designer. This structure is then fed into CA with solar radiation data as seeds that analyse and calculate the accumulated incidences over the aggregation elements. Lastly, a Genetic Algorithm (GA) is used to optimise the numeric values (the shape-driving parameters against the solar analysis), to find the optimal shape for the particular solar problem. The whole process is computationally intensive, with a solution for a given location and context taking hours to be found; with 1000 evolutions taking up 70Gb of data.

To automate this process, and carry its human-machine interaction biases, we chose to use pix2pix ML - a conditional Generative Adversarial Network (GANs) for image-to-image translation that learns how to transform one input image into a corresponding output image following a given pattern (Isola, et al., 2017). The strategy is to use our design and optimisation algorithm as the pattern that pix2pix should learn. This is achieved by generating an image that represents the input - the context of the building and the area it should occupy on the plot, with one image of pixels being exported by each layer of voxels (as to slice a 3D shape into a stack of layers). Then, the CA analyser runs and finds the best, optimised solutions it can; from which, new images are generated, representing each layer of the solution, with the position of the resulting voxels marked as pixels.

These images, combined with the first set, form pairs in the dataset that is used to train the pix2pix, one representing the input (context and shape location) and the other representing the output (an aggregation of voxels). The generative and discriminative models in GANs compete against each other until equilibrium. Once the ML algorithm has been trained, it is presented with a not-before-seen set of images of a context, and nearly instantaneously produces the output set of images that can be used to construct the 3D aggregation of the voxels, optimised for solar incidences in that given location.

3.2. Preliminary Results

The result is a combinatorial strategy of rule/agent-based and ML intelligence. As opposed to manually supervising the ML in learning, CA was employed as an instructor of the learning process. This largely accelerated the optimisation processes from hours and hundreds of Gb of data to just minutes with a fully-trained ML. It may be used to automate the generation of many aggregative possibilities to win over complex, dynamic solar conditions in the built environment.

The CA-GA feedback is designed to automate a generative process that takes objective (location, context and analysis) and subjective inputs (designer's parametric model). The challenge was computational costs from 3-dimensional data analysis. ML intelligence compresses high-dimensional data into linear space that predicts the results of this process when shown a new starting point. Normally, such compression results in the loss of integrity in the geometry; nonetheless, voxels acting as proxies for complex geometries, generating not forms but distribution protocols. For anyone who seeks to automate optimization, while keeping the complexity of intuition-based biases as part of the generative process, similar pipelines can be customized for other problems (beyond solar) asked to a machine, without directly programming how it should operate.

The figures below show the output aggregation strategies. The next step is to explore evaluating metrics based on laws of entropy and power scaling to rationalise and review output. From which, it must be discussed how the mathematical logic of a unit form can be synthesised with CA logics to inform one another, not simply as form information, but as mathematical data. One instance is to translate form-finding models to become parametric by forcing morph cages in grasshopper for the link with GA, so as to add virtually any continuous shape instead of just parametric definitions.

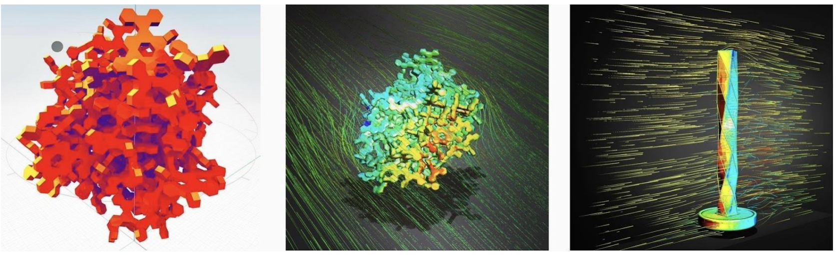

Figure 2. 'AI in+form' workshop by @r.e.ar (2021). *A test on aggregation of building elements using rule/agent-based AI cellular automata (CA) and genetic algorithm (GA) for optimization based on solar data.*

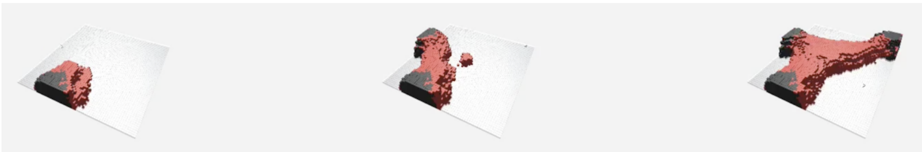

Figure 3.'AI in+form' workshop by @r.e.ar (2021). *Pix2pix ML algorithm trained on aggregation output from CA-GA, a significant gain in computational time and power by iteratively translating pixel-voxel.*

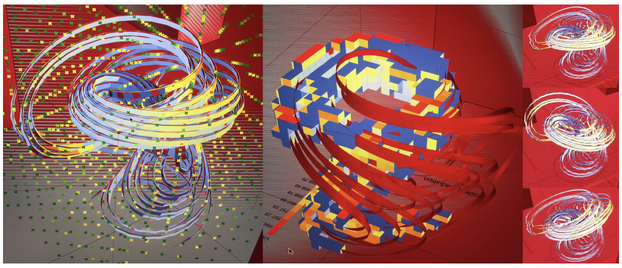

Figure 4. 'AI in+form' workshop by @r.e.ar (2021). *Each voxel data point acting as geometry proxies, is replaced with continuous geometry of a solar design, which is going through GA evolving into iterations based on solar data.*

3.3. Design Output

As the primary theoretical framework, this pipeline has been structured from a human interaction design process to a machine-supported design workflow, understanding the process-specific inputs and outputs of each step and transferring the correct data from one node to another.

In that sense, the pipeline allows design flexibility inside each node, being quite adaptable according to the design problems to be addressed depending on the study cases. This idea has been based on the principle coming from the "Universal Constructor" developed by John and Julia Frazer (1990). Data can be represented under this concept in any possible scale and shape inside an experiment (in that case, a set of translucent boxes). In our approach, digital voxels replace physical boxes as information containers that are getting information from a more human-based step to the next one, in a gradually more automated way of design. Still, the data can always be something different, enriching the entire workflow, creating speculative variations over the same original study case, as we can appreciate in the following examples.

Media 1. ´AI in+form' workshop by @r.e.ar - Tomasow R., Pillaca G., Qian Y. (2021).

TimeLapse video showing the pipeline, access:
https://www.instagram.com/tv/CNRNY42lYmM

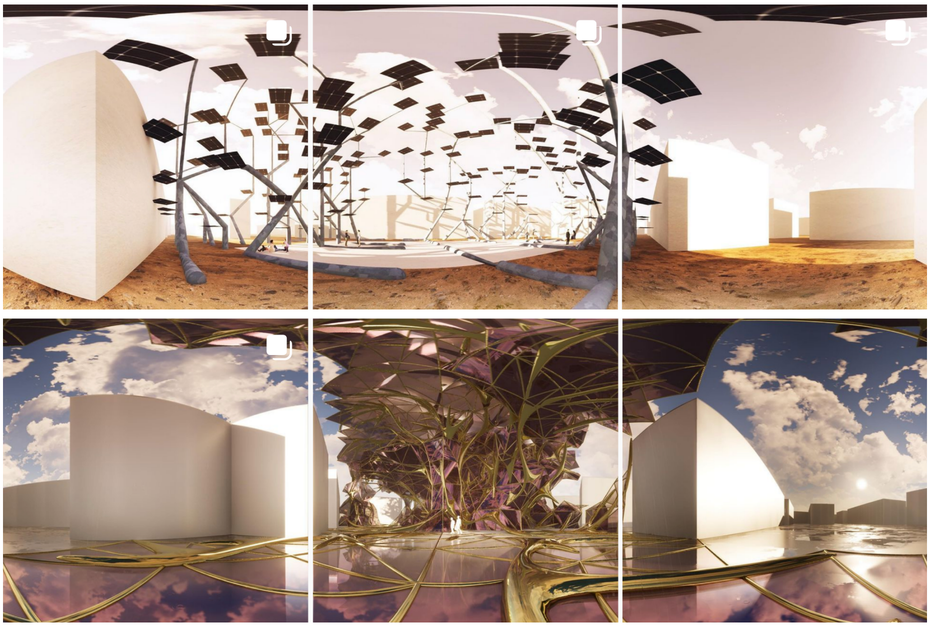

Figure 5 & 6. 'AI in+form' workshop by @r.e.ar - Tomasow R., Pillaca G., Qian Y. (2021). *Two design variations coming from the same pipeline, solar dataset, and trained AI algorithms*.

In both examples (fig 5 and fig 6), our students faced the same problem as initial input, including sharing precisely the same environmental data from a coastal community located in Perú. But later, after running the first set of design iterations, both teams finally delivered variations from each node to the next one, creating entirely different results both in shape, density and architectural programme at the end of the whole pipeline. Using the same principles (as well as the CA and GA use), the translation of these set of information was reinterpreted by both teams in different ways, due to the initial conceptual reference and human-based exploration created a divergence finally in the result, being one case based more on algae growing optimized shape for solar radiation capture (fig 5). The other (fig 6) presented a more structural and three based shape for the same principle but mixed with a community football field as specific programmatic use, generating more rigid design constraints that affected the whole process from human to machine design workflow.

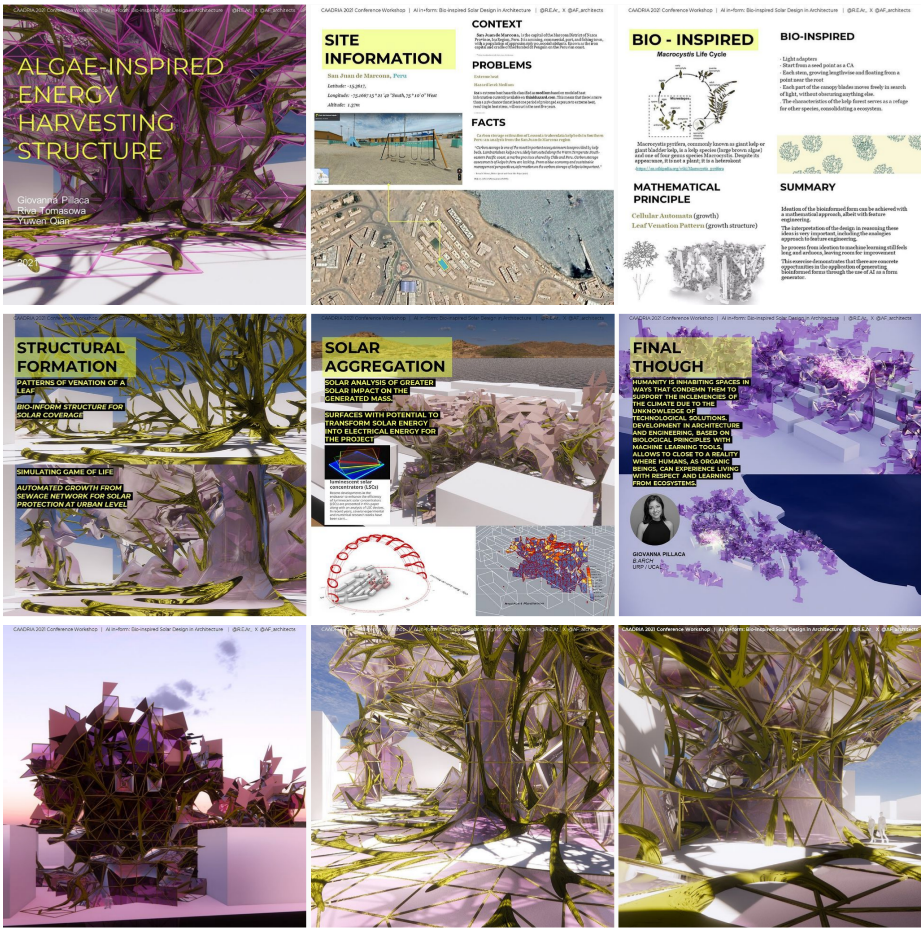

Figure 7. ‘AI in+form’ workshop by @r.e.ar - Tomasow R., Pillaca G., Qian Y. (2021). I*s it possible to have light harvesting structures that are transparent? A Luminescent Solar Concentrator (LSC) can be fabricated as flexible thin films, light bounces up and down within the material, transporting solar energy to the edge of a panel to the solar cells, and freeing up the surface for transparency. This gives new opportunities of turning large areas of buildings in cities as light harvesting surfaces, liberating solar energy systems from being merely on the roof, but on building corners unused, against reflective surfaces, and even indoors. Exploring the modest renewable energy capacities within urban contexts.*

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4. Conclusion

This research tries to understand how socioeconomic and sociobiological systems have been achieving their respective versions of scaling and aggregation. Afterwards, it translates such principles into building design, which defines architecture as a process of information feedback between various forms of intelligence.

This research frames design as iterative decision-making processes that feedback between input/output of human-machine, which demands a studying of tasks within a design process and how they can be distributed between designers/algorithms that are each better at different tasks. More specifically, this research studies the practise of negotiation between designer intuition and machine intelligence, informed by AI, which can take forms of 'rule/agent-based' (i.e. cellular automata CA, genetic algorithm GA) and 'machine learning' systems (i.e. pix2pix Generative Adversarial Networks GANs). The former becomes an instructor in supervising the training of the latter. Through both theoretical and technical means, this paper hopes to prompt discussions around the relationship between nature/human/machine and the future roles of architects as designers.

The proposed pipeline was tested preliminarily through a series of workshop, in which, participant develops a critical understanding towards the various computational intelligence, including cellular automata and machine learning, and adopt our combinatorial production pipeline to the specificity of their solar design, producing not final results but variational output.

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