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Utilizing Artificial Intelligence Techniques in Complex Form Generation

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Abstract**:** Architects have always aimed at developing more adequate software to capture the complexity of biological self-organizational systems in architectural form generation. Agent-based modeling (ABM) emerged as a promising approach, where agents can exhibit emergent self-organizing behavior. However, the nonlinearity and feedback loops typically associated with natural systems are not quite achieved using traditional ABMs. This paper investigates the integration of reinforcement learning (RL) - an artificial intelligence technique - to develop reinforcement learning ABMs to enhance architectural form generation. Decentralized multi-agent reinforcement learning is proposed as an approach where agents learn complex strategies that maximize rewards through interactions with the environment to model emergent structures that are typical characteristics of natural systems. The paper reviews relevant biological self-organization concepts that inform architectural objectives, surveys previous ABM research, and proposes a RL framework that provides a systematic approach for developing RL models that capture the complexity and adaptability of natural systems, focusing on architectural form generation.

Keywords: Artificial Intelligence, Form Generation, Complex Systems, Agent-based Models.

1. INTRODUCTION

During the early 1950's, multiple trials emerged to digitalize architecture through successive evolutions, starting with Modularity, Computational Design, Parametricism, and finally Artificial Intelligence[1]. AI was defined by J. McCarthy as "using the human brain as a model for machine logic"[2]. Architects have always aimed to develop more adequate software to integrate nature complexity into form generation. Eventually, by blending statistical computing with computational design, machines were enabled to grasp complexity and build an "intuition" to solve problems or make architectural decisions [3].

The introduction of statistical computing has raised research interest for multiple governments, and institutions, aiming at the intersection of seemingly disparate research areas within subfields. This paper seeks a collaborative approach between architectural research in AI, which encompasses targeted subdisciplines such as machine learning and multi-agent complex systems, aiming to learn from nature complex systems in terms of adaptive forms. Generative emergence was first defined by John H. at Oxford University in 1998, "We are everywhere confronted with emergent complex adaptive systems, ant colonies, neurons ...where the behavior of the whole is much more complex than the behavior of the parts"[3].

2.AIMS AND METHODOLOGY

The main aim of this paper is to investigate the potential of machine learning interventions in architectural form generation, with specific focus on Reinforcement Learning (RL) intervention in agent-based models (ABM). The paper first discusses background related to biological self-organization systems at the organism level to understand potentials and parameters in biological self-organization systems, followed by a review of previous research related to agent-based modeling self-organizational form generation to understand the potentials and limitations in previous models. Finally, the paper discusses the potential of artificial intelligence RL intervention in ABM form generation, and proposes a framework for RL in architectural form generation and its limitations, taking into account the different parameters and constraints of biological self-organization systems.

3.BIOLOGICAL SELF-ORGANIZATION SYSTEMS

Yates et al. [4] and Holland [5] are major contributors to self-organizing systems, focusing on emerging concepts like mathematical models, game theory, computer-based models, and neural networks. Self-organization in biological systems differs from physical and chemical systems due to the rules governing interactions among components. Understanding the complexity of social biological systems adds to the architectural understanding of where decision-making, synchronization of activities, and the surrounding environment impact the emergent patterns. As shown in Figure 1, self-organization systems at the organism biological level can be categorized based on behavior and collective by-products, allowing for a more accurate assessment of architectural objectives. As shown in Figure 2, examples include collective construction, swarming, pattern formation, neural systems, and evolutionary systems[6][7]. This paper focuses on social complex systems in collective construction and swarming due to their high response to environmental signals, which can increase the flexibility and variety of collective patterns they build [6].

Fig 1 Levels of biological organizations.

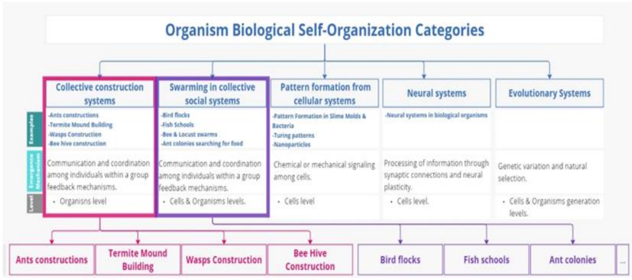

Fig 2 Organism Biological Self-Organization Categories.

The organism level is closely related to architectural ABMs, as organisms can create complex structures and behaviors through simple interactions. Emergent biological multi-agent complex systems, like wasps or termites, are structured bottom-up, incorporating environmental, structural, and functional aspects.

Positive and negative feedback are essential in self-organizing systems to regulate fluctuation, stabilize processes to prevent chaos[4]. Positive feedback amplifies behavior, leading to exponential growth and emergent patterns, Such as Positive feedback in a flock of birds changing directions, and negative feedback maintains safe spacing to prevent collisions, as shown in Fig 3.

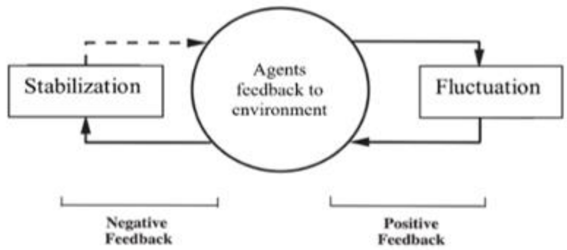

Fig 3 Self-organizing systems, both positive and negative feedback

Complex emergent models exceed the typical notion of architectural form generation. Systems have the capability of self-organization defining new levels of complex behavior in a nonlinear manner of individuals (agents), displaying higher-level integration, functionality, and adaptation based on the evolutionary process of continuous adjustments in micro-events and feedback loops over time from the system to its environment, capitalizing 'efficiency' and 'optimization'[4][5][6].

4.ABM SELF-ORGANIZATIONAL FORM GENERATION

Agent-based modeling (ABM) is a powerful computational tool that can simulate the behavior of agents. ABM has been applied in various fields, including architecture, to model self-organizing systems and emergent behaviors. Biologists, biomimetic engineers, and computer scientists have already tackled the field of computing the self-organized ABM, and used it as a problem-solving or optimization method in real-life problems [8]. ABMs have been used in various architectural applications such as simulation and form generation, where agents can represent design elements such as building components or environmental factors. By defining rules and constraints for the agents, the ABM can generate emergent patterns and structures that exhibit complex self-organization [9].

Throughout the last decades, many architectural digital tools were developed aiming to digitalize natural patterns such as rule-based logic, ABMs, Or coupling ABMs with heuristic algorithms for optimization [10][9]. Research related to ABM tools, including Steven [11], Franziska [8] and Manzo [12], reveals that ABM software development remains a significant barrier to generating complex behavior that occurs in nature. Architectural digital tools have been developed to digitalize natural patterns, but traditional rule-based logic is mostly incapable of simulating complex behavior [8][11]. Typical rule-based logic generally fails to simulate complex behavior, lacking crucial properties such as non-linear dynamics, true environment understanding and feedback loops, and efficient resource allocation, accordingly altering a set of rules per time. As for ABM tools, the level of abstraction in the inputs and feedback does not achieve the complexity needed for achieving developed architectural forms, which is a post-design decision and does not inform the process from the beginning. This often results in homogenized forms that do not satisfy basic architectural constraints such as structural, environmental and functional aspects. Accordingly, the increasing complexity over multiple design layers of ABM tasks makes the process difficult to be interpreted with pre-programmed rules, which brings computational architecture toolset towards AI [13].

5.AI REINFORCEMENT LEARNING INTERVENTION IN ABM FORM GENERATION AND PROPOSED FRAMEWORK

Artificial intelligence, coined by John McCarthy in 1956. Machine learning (ML) is AI that enables computers to learn without explicit programming, using neural networks inspired by the human brain. Deep Neural Networks (DNNs) are artificial neural networks with interconnected layers designed to process complex data [14], as shown in Fig 4. Researchers have classified AI into four main learning types: supervised, unsupervised, semi-supervised, and reinforcement learning [1][15], as shown in Fig 5

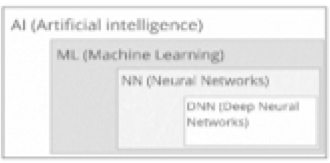

Fig 4 Relationship between AI, ML, NN & DNN [16]

Fig 5 Machine learning types: Unsupervised Learning (UL), Supervised Learning (SL),

Semi-Supervised Learning (SSL), Reinforcement Learning (RL) [17] (edited by researcher).

There is a rapid research advancement exploring the potential of integration of machine learning and architecture using supervised and unsupervised algorithms, such as architectural classification [14], plan generation [18], stylized architecture [1], and urban design and planning [19].

Unsupervised or semi supervised learning are mostly used in labelling data such as labelling plan spaces in plan generation applications [18], One of the most used methodologies in architectural form generation are unsupervised generative adversarial neural networks (GAN). Zhang [20], used Style GAN to use stylized plans and sections to learn and build stylized 3D models, **Fig 6**. However, the generated forms didn't address the main architectural building components nor special qualities, Although the continuous attempts of researchers to take 2D views classification and generation a step further to 3D, where 3D translation occurs in late stages of the generative process.

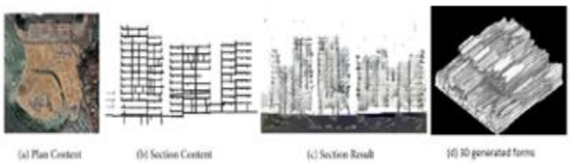

Fig 6 Style GAN to generate stylized plans and sections to build stylized 3D models [20].

Imdat et al. [21] merged both supervised labelled plans as input data data which then converged to unsupervised GAN model to generate entirely new designs, as shown in **Fig 7**. It is clear that there is a lack of information to provide a model for form generation dealing with natural complexities using AI, and training DNNs to evaluate 3D spaces [21]. It is also obvious that there is a lack of architectural research addressing reinforcement learning (RL) and its potential in dealing with form generation multi-agents.

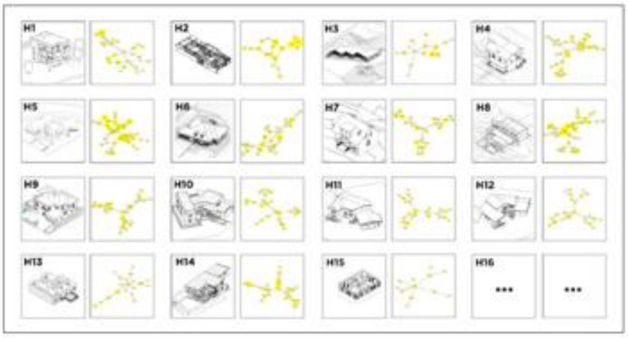

Fig 7 home design samples generated in axonometric and graph view [21].

RL has significantly contributed to the field of AI since 2015 [22]. RL trains machine learning models to make a sequence of decisions, which enables RL methods to drive optimal strategies for agents [13]. Deep reinforcement learning (DRL) uses multi-layer neural networks to solve a problem in different levels of high-dimensional data, where agents compete or cooperate to provide optimal solutions and maximize the task completion success based on self-learning strategies [12][13]. This qualifies RL as a promising approach to solve complex real-world problems in multiple fields such as multi-player games, surveillance, drones, and architecture [12].

RL can help overcome the limitations of traditional ABMs in architectural form generation by enabling agents to learn and adapt to the environment in real-time and optimize objectives through rewards and Markov Decision Process [23].

Reinforcement learning (RL) has the potential to enhance the capabilities of ABMs and enable the generation of more complex and optimized architectural forms due to its heuristic mode, incorporating meta-heuristic characteristics without human knowledge, and its sequential decision-making approach, making it suitable for evolving generative processes. Although a few researchers have explored the integration of RL training into architecture, such as field sensing robot swarms, and layout shape grammars [24], there is very little in precedent literature within architectural research that has addressed the potential of RL in dealing with multi-agent ABM and form generation.

Wang and Snooks [25], **Fig 8**, proposed an RL single agent Random Walk Formation approach, applied to a case study exemplified the concrete effects and potential flexibility of cultivating intuitions for generative systems. Their research highlighted the importance of the future research trajectories to further develop the multi-agent self-organizational generative approach.

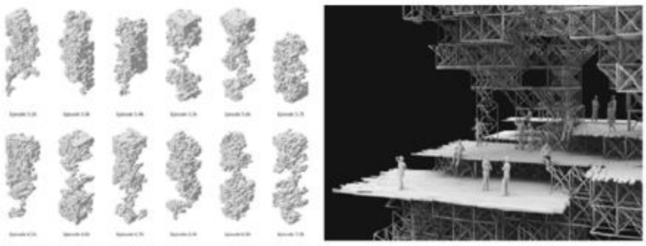

Fig 8 RL single agent Random Walk Formation approach, training outcome samples [25].**Error! Reference source not found.**. the state represents the current environment snapshot observed by the RL agent. The agent starts by taking an action, then receives a scalar reward that evaluates the quality of the action and guides the agent towards better outcomes. The policy, which is a function that maps observation states to actions, is learned by the agent, either deterministically or stochastically. The goal of the agent is to learn a policy that maximizes the expected reward over time, enabling it to make optimal decisions in complex environments [14]

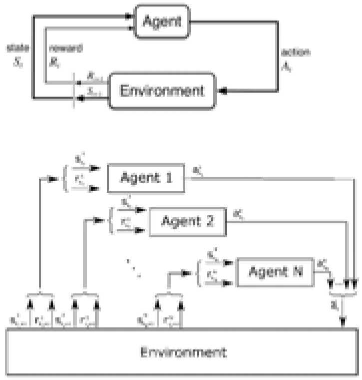

Fig 9 RL consists of three main components: state "S", reward "R", and action "A". *Top*: Single-agent RL, *Bottom*: Multi-agent RL [26]

RL can be implemented using either a single agent or multiple agents. Single-agent RL involves a single agent interacting with an environment to learn a policy that maximizes its expected reward. On the other hand, multi-agent RL involves multiple agents interacting with each other and the environment to learn a joint strategy that maximizes the collective reward. Similarly, RL can be implemented in a centralized or decentralized manner. Centralized RL involves a single agent or a centralized controller that makes decisions for all agents, while decentralized RL allows each agent to make its own decisions based on local observations and rewards.

The choice of single vs. multi-agent and centralized vs. decentralized reinforcement learning depends on the problem. Self-organizing complex problems, such as the flocking or the formation of ant colonies, typically involve multiple agents interacting with each other and the environment to produce emergent structures. In these cases, multi-agent decentralized RL is more appropriate. However, for problems that can be solved by a single agent or require centralized control, single-agent and centralized RL may be more suitable. Overall, the selection of the RL approach should be based on the problem's characteristics and requirements [14], as shown in Fig 10.

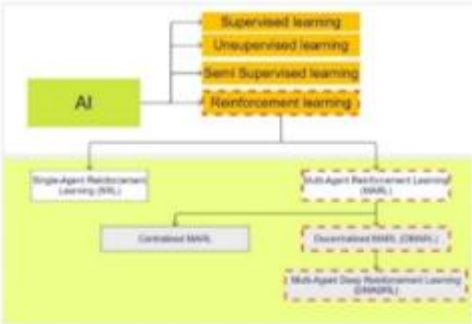

Fig 10 Reinforcement learning model selection according to the problem.

The proposed framework for developing a reinforcement learning model for self-organizational form generation inspired by natural systems such as swarm behavior or insect nest construction, involves several key steps. Firstly, a comprehensive understanding of the specific natural system is gained, including its characteristics, behavior, and patterns, to extract relevant parameters that will inform the model. Accordingly select an appropriate learning type for the reinforcement learning model. The framework suggests using decentralized multi-agent deep reinforcement learning (DMA-DRL) to model decentralized control and emergent structures observed in collective construction systems and swarming in social natural systems.

The appropriate algorithm is chosen based on the specific problem. Factors such as problem complexity and desired outcomes guide the choice of RL algorithm. With the algorithm selected, the RL model is formulated, defining the properties and parameters of the agents. In form generation, each agent represents a building component with properties like position in 3D environment, size that will influence building unit, shape which can be predefined or learned, communication type with nearby agents, and memory. These properties determine the architectural characteristics. Agents can interact and collaborate within their influence radius, exchanging information or coordinating actions. Agent input parameters such as learning rate, exploration vs. exploitation balance, influence radius, thresholds, and action space, control how agents update their knowledge, explore new possibilities, interact, and trigger specific actions.

The next step is training the model using the selected algorithm and input variables according to the natural system. The model is exposed to the environment, and agents learn from their interactions to maximize rewards based on specified objectives. Iterative updates and adjustments improve the model's performance. Visualization and evaluation help assess how well the RL model captures the complexity and adaptability of the natural system. However, there are some limitations related to machine power and the tendency of the model to generate black box unpredictable outputs, which can be further discussed in future research [27].

Fig 11 illustrates the application of this framework in developing reinforcement learning models for complex natural systems. The specific implementation details and examples depend on the studied natural system and the objectives of architectural form generation.

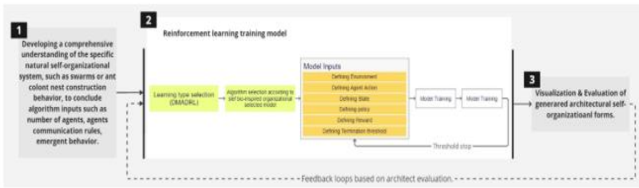

Fig 11 Proposed Reinforcement learning framework to solve complex multi-agent problems.

6.CONCLUSION

This paper investigated the potential of integrating reinforcement learning techniques into agent-based modeling frameworks for architectural form generation. The limitations of traditional rule-based ABM approaches were reviewed, including the inability to achieve the nonlinearity, adaptation, and feedback loops exhibited in biological self-organizing systems. RL framework was proposed as a machine learning approach that could enhance the capabilities of ABMs by enabling agents to learn optimal strategies through interaction with environment.

The key concepts of biological self-organization at the organism level were outlined, focusing on decentralized control, and simple local interactions leading to complex global behaviors. These biological principles informed the architectural objectives for achieving adaptive, optimized forms. A review of previous computational form generation methods established the need for more advanced AI techniques like RL.

A conceptual framework was presented for integrating decentralized multi-agent RL into ABM architectural models. This involves understanding the target natural system, selecting appropriate RL algorithms, formulating the RL-ABM model, training, and evaluating the generated forms. The trained RL agents would learn to self-organize and adapt to produce architectural configurations.

In conclusion this research explores a novel form generation approach using AI advances and bio-inspired multi-agent models. It aims to develop architectural model that captures natural complexity. Further work is needed to validate the framework on specific case studies and shift the model from black-box to grey-box.

REFERENCES

[1]. Chaillou S. *AI + Architecture | Towards a New Approach* [M.S. thesis]. Harvard University.; Harvard University. 2019.

[2]. McCarthy J. *Defending AI Research*. Review Literature And Arts Of The Americas.

[3]. Hensel M, Menges A, Weinstock M. *Techniques and Technologies in Morphogenetic Design*. Vol. 76, Architectural Design (AD). London:Academy Press, 2006.

[4]. Yates FE. *Self-Organizing Systems, The Emergence of Order*. Self-Organizing Systems. Springer, 1987.

[5]. John H. Holland. *Emergence: From Chaos to Order*. Vol. 74, The Quarterly Review of Biology. Oxford University Press, 1998.

[6]. Anderson, Philip W., Joshua M. Epstein, Duncan K. Foley, Simon A. Levin MAN. *Self-Organization in Biological Systems*. Princeton University Press, 2001.

[7]. Floreano D, Mattiussi C. *Bio-Inspired Artificial Intelligence*. The MIT Press Cambridge, Massachusetts, 2008.

[8]. Klügl F, Bazzan ALC. Agent-based modeling and simulation. *AI Magazine*. 2012;33(3):29–40.

[9]. Chen Y. *Swarm intelligence in architectural design* [M.S. thesis]. University of California, Berkeley.; 2015.

[10]. Eberhart RC, Shi Y. *Computational Intelligence: Concepts to Implementations*. Vol. 6, Computational Intelligence: Concepts to Implementations. 2007.

[11]. Lytinen SL, Railsback SF. Agent-based Simulation Platforms: An Updated Review. *EMCSR*. 2011;82(9).

[12]. Manzo G. Potentialities and limitations of agent-based simulations: An introduction. *Revue Francaise de Sociologie*. 2014;55(4):653–88.

[13]. Nguyen TT, Nguyen ND, Nahavandi S. Deep Reinforcement Learning for Multiagent Systems: A Review of Challenges, Solutions, and Applications. *IEEE Transactions on Cybernetics*. 2020;50(9):3826–39.

[14]. Lapan M. *Deep Reinforcement Learning Hands-On.2nd Ed.* Birmingham:Packt, 2018.

[15]. McCarthy J. *Defending AI research : a collection of essays and reviews*. McCarthy J, editor. Review Literature And Arts Of The Americas. Center for the Study of Language and Information, 1996.

[16]. Alkabbani H, Ahmadian A, Zhu Q, Elkamel A. Machine Learning and Metaheuristic Methods for Renewable Power Forecasting: A Recent Review. *Frontiers in Chemical Engineering*. 2021;3(April):1–21.

[17]. Reinforcement Learning - simply explained! | Data Basecamp. 2022 [Accessed 2023 Feb 18]. Available from: https://databasecamp.de/en/ml/reinforcement-learnings

[18]. Eltarabishy S. *Towards Data-Driven Design : Leveraging open data and deep learning in symbol spotting for furniture layout planning* [M.S. thesis]. UCL.; 2017.

[19]. Del Campo M. Architecture, Language and Ai. *Proceedings of the 26th International Conference of the Association for Computer-Aided Architectural Design Research in Asia, Volumn 1*. 2021;1:211–20.

[20]. Zhang H. 3D Model Generation on Architectural Plan and Section Training through Machine Learning. *Technologies*. 2019;7(4).

[21]. As I, Pal S, Basu P. Artificial intelligence in architecture: Generating conceptual design via deep learning. *International Journal of Architectural Computing*. 2018;16(4):306–27.

[22]. Mnih V, Kavukcuoglu K, Silver D, Rusu AA, Veness J, Bellemare MG, Graves A, et al.. Human-level control through deep reinforcement learning [internet]. *Nature*. 2015;518(7540):529–33.

[23]. Sutton RS, Barto AG. *Frontiers (in Reinforcement Learning: an introduction learning)*. Mit. 2018.

[24]. Ruiz-Montiel M, Boned J, Gavilanes J, Jiménez E, Mandow L, Pérez-De-La-Cruz JL. Design with shape grammars and reinforcement learning. *Advanced Engineering Informatics*. 2013;27(2):230–45.

[25]. Wang D, B RS. Artificial Intuitions of Generative Design: An Approach Based on Reinforcement Learning [internet]. *Proceedings of the 2020 DigitalFUTURES*. 2021;189–98. Available from: http://dx.doi.org/10.1007/978-981-33-4400-6_18

[26]. Chincoli M, Liotta A. Self-learning power control in wireless sensor networks. *Sensors (Switzerland)*. 2018;18(2):1–29.

[27]. Ribeiro MT, Singh S, Guestrin C. "Why Should I Trust You?" Explaining the Predictions of Any Classifier. *Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Proceedings of the Demonstrations Session*. 2016;97–101.