An Architectural Framework for Distributed Semi-Autonomous Construction

Using Reinforcement Learning to Support Scalable Multi-Drone Construction in Dynamic Environments

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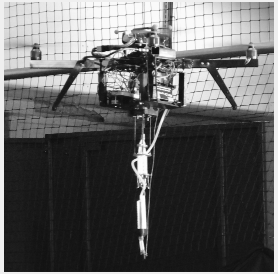
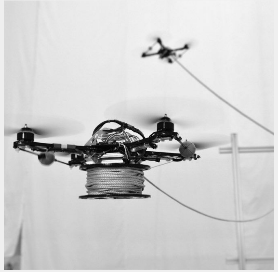
Frame structure [1]

Bricklaying [2]

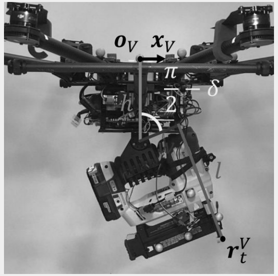


3D printing [3]



Tensile weaving [4]

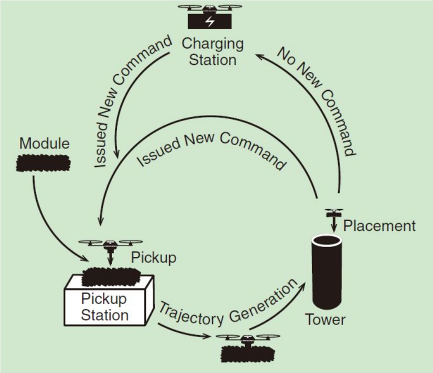
Masonry construction [5]

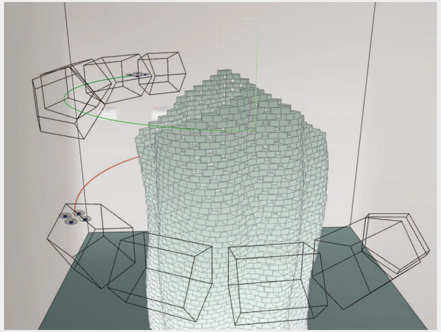


Roofing [6]

Drones In Fabrication/Making

[1] Lindsey, Quentin, Daniel Mellinger, and Vijay Kumar, 2012.
[2] Augugliaro, Frederico, Sergei Lupashin, Michael Hamer, Cason Male, Markus Hehn, Mark W. Mueller, Jan Sebastian Willmann, Fabio Gramazio, Matthias Kohler, and Raffaello D'Andrea. 2014.
[3] Hunt, Graham, Faidon Mitzalis, Talib Alhinai, Paul A. Hooper, and Mirko Kovac. 2014.
[4] Ammar, Mirjan. 2016.
[5] Goessens, Sébastien, Caitlin Mueller, and Pierre Latteur. 2018.
[6] Romano, Matthew, Yuxin Chen, Owen Marshall, and Ella Atkins. 2019.



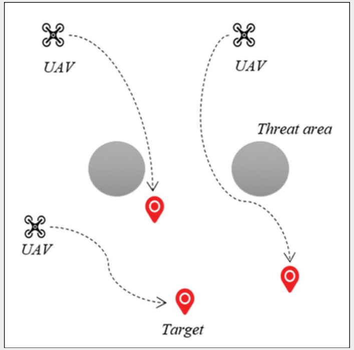


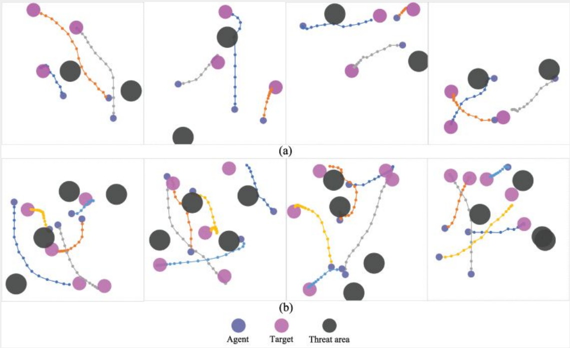
The Flight Assembled Architecture*

- Four drones building a 6-m-tall foam tower
- Propose pick-place state machine
- Approach hard to scale up
- Assume perfect knowledge of environment

Case Studies

* The Flight Assembled Architecture Installation. Augugliaro et al., 2014.





Joint Optimization of Multi-UAV Target Assignment and Path Planning Based on Multi-Agent Reinforcement Learning*

- Real-time drone target assignment and path planning
- Based on MADDPG
- Agent-level observation
- Approach hard to scale up

Case Studies

* Joint Optimization of Multi-UAV Target Assignment and Path Planning Based on Multi-Agent Reinforcement Learning.Qie, H. et al. 2019.

Major Limitations

- Lack of generalizability and scalability.
- Perfect knowledge of the environment assumption
- Environmental and socio-technical complexity of design-construction sites

Limitations

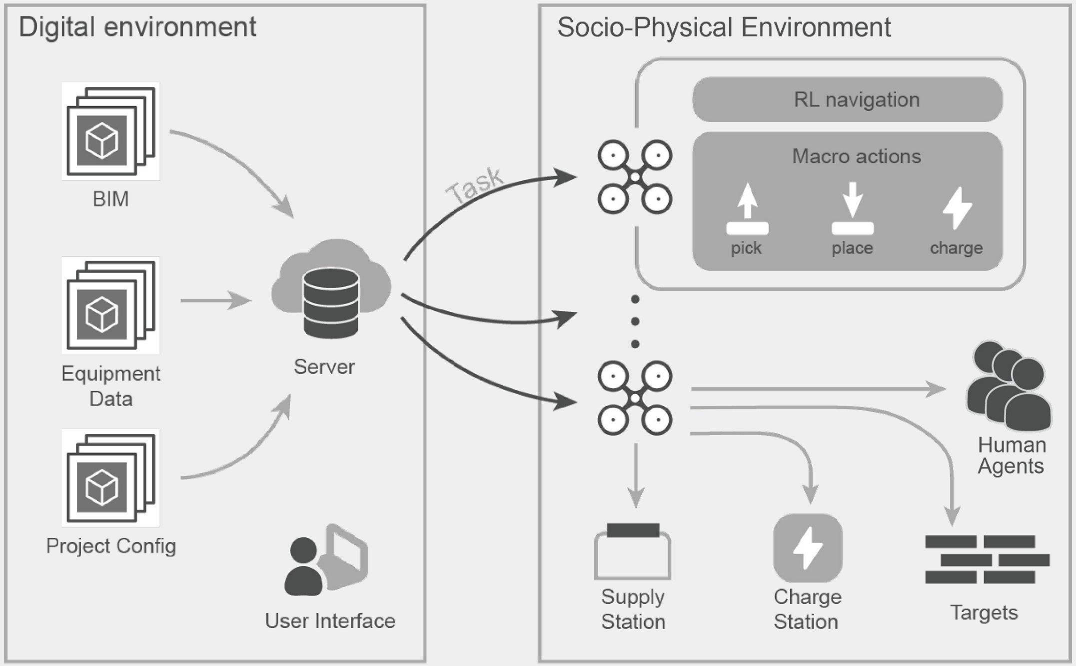
How to coordinate an uncertain number of drones for additive construction tasks in dynamic environments, as part of an integrated human-machine construction workflow?

Research Question

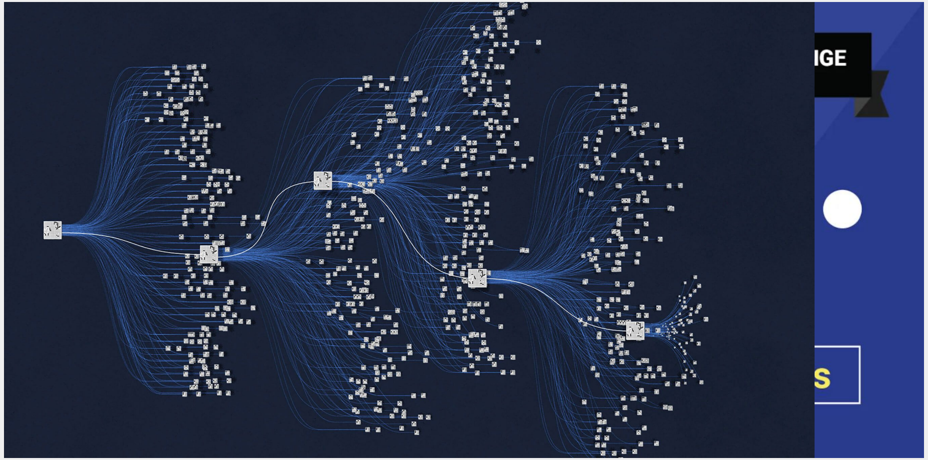
A decentralized reinforcement learning control framework based on sensory input with a central server for dispatching tasks can support multi-drone coordination for architectural construction, and thus enable more complex human-machine construction processes.

Hypothesis

Method



Technical Framework



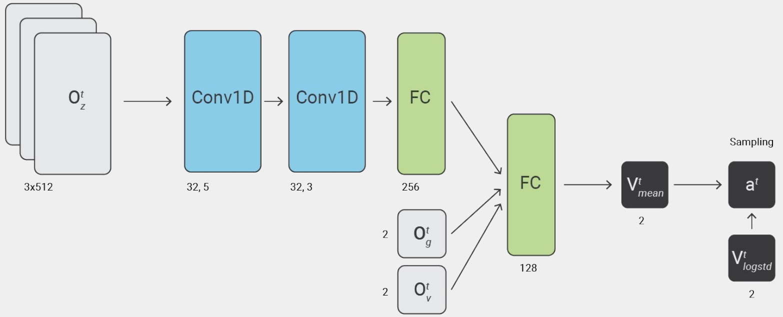
Reinforcement Learning (RL)

- Training of machine learning models to *make a sequence of decisions*. The agent learns to achieve a goal in an uncertain, potentially complex environment.

- It is concerned with how agents take actions in an environment in order to *maximize the notion of cumulative reward*.

Path Planning and Control

* AlphaGo, AlphaZero, AlphaGo in China, (2017).
** Images from: https://deepmind.com/alphago-china & https://www.alphagomovie.com/



Architecture of Neural Network*

RL Algorithm Details

- Policy-gradient algorithm, **PPO** (Proximal Policy Optimization) to learn an optimal **collision avoidance** policy.
- The architecture of policy network takes lidar, goal position and velocity as observation (input).
- We use convolutional layers to preprocess lidar input.

Path Planning and Control

* Reproduced from Long, Pinxin, et al. "Towards optimally decentralized multi-robot collision avoidance via deep reinforcement learning." 2018 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2018.

Algorithm 5 PPO with Clipped Objective

Input: initial policy parameters θ_0, clipping threshold ϵ
for $k = 0, 1, 2, ...$ **do**
  Collect set of partial trajectories $\mathcal{D}_k$ on policy $\pi_k = \pi(\theta_k)$
  Estimate advantages $\hat{A}_t^{\pi_k}$ using any advantage estimation algorithm
  Compute policy update

$$\theta_{k+1} = \arg\max_{\theta} \mathcal{L}_{\theta_k}^{CLIP}(\theta)$$

  by taking K steps of minibatch SGD (via Adam), where

$$\mathcal{L}_{\theta_k}^{CLIP}(\theta) = \mathop{\mathrm{E}}_{\tau \sim \pi_k}\left[\sum_{t=0}^{T}\left[\min(r_t(\theta)\hat{A}_t^{\pi_k}, \mathrm{clip}\left(r_t(\theta), 1-\epsilon, 1+\epsilon\right)\hat{A}_t^{\pi_k})\right]\right]$$

end for

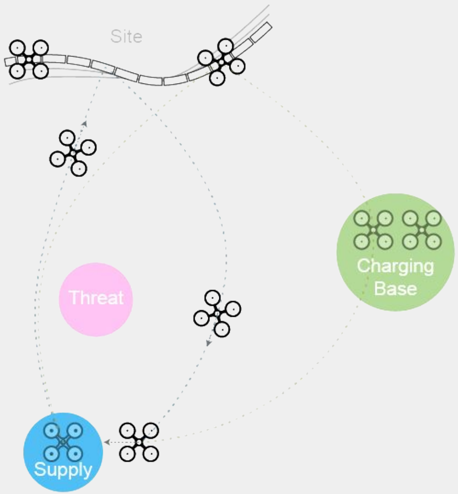
PPO Algorithm*

RL Algorithm Details

- We use clipped objective for proximal policy update.
- We use a decentralized approach which is scalable for multiple drones.

Path Planning and Control

* Achiam, Joshua. "Advanced policy gradient methods." (2017).

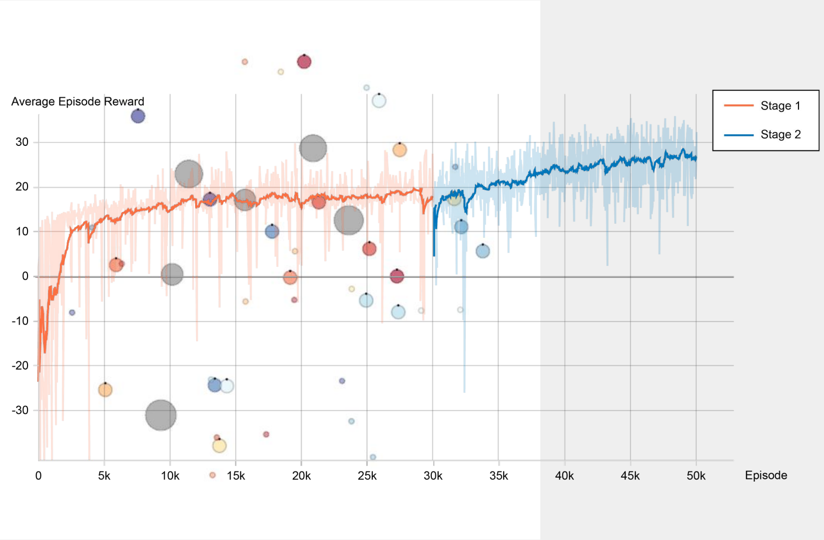


RL Scenario

- A given environment
- A set of agents
- A set of bases (charging, resupplying)
- A set of targets
- A set of threat areas

- The agents should navigate to the designated targets while avoiding obstacles and other agents on the 2d plane.

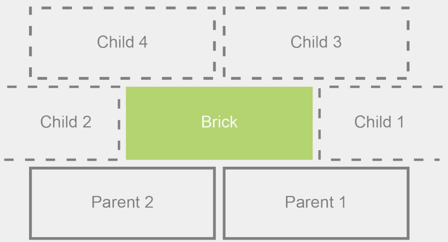
Path Planning and Control



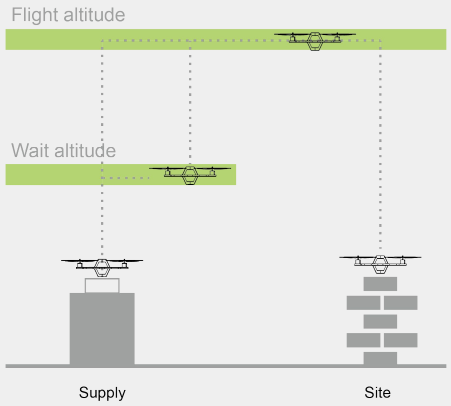
Training the Model

- Two-stage training, curriculum learning:
  - 1st: 5 agents
  - 2nd: 10 agents + threat areas
- Evaluation:
  - 20 agents

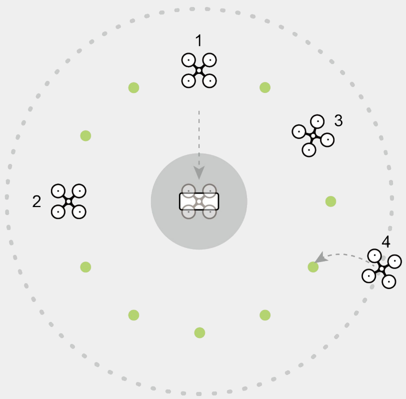
Path Planning and Control



Brick order design

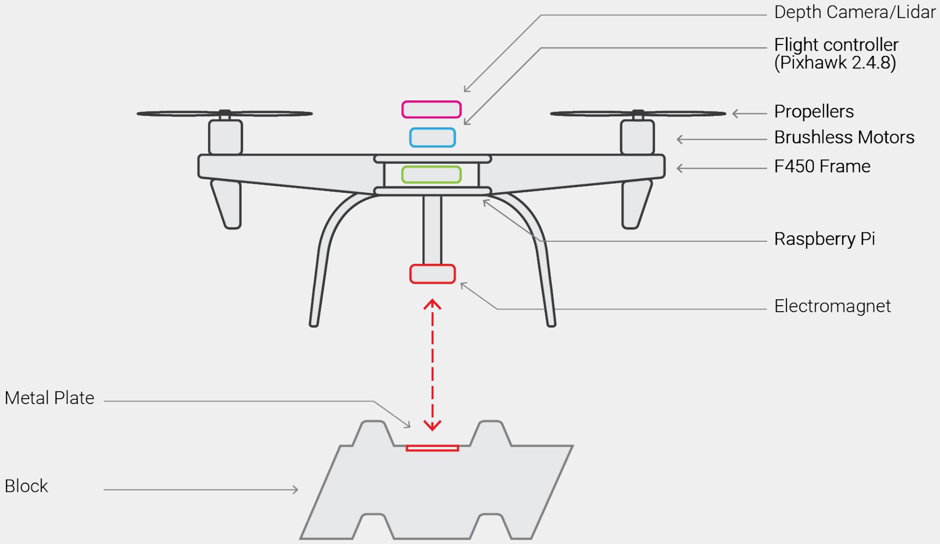


Altitude management



Waiting mechanism

Multi-drone Coordination



Drone Setup

- Current state
- Complete setup

Drone Hardware

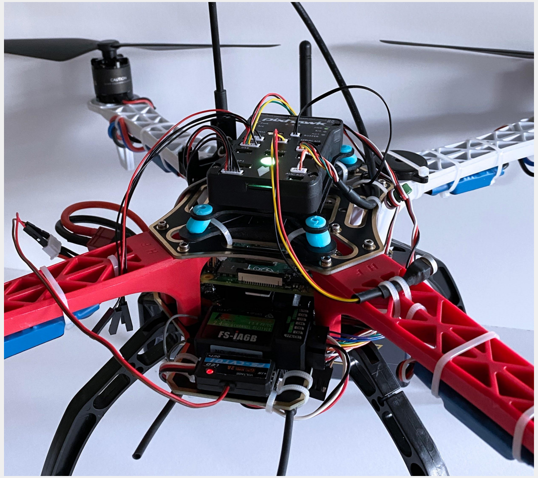
Drone Hardware (WIP)

Frame
- F450

Control
- Pixhawk 2.4.8
- Raspberry Pi 4

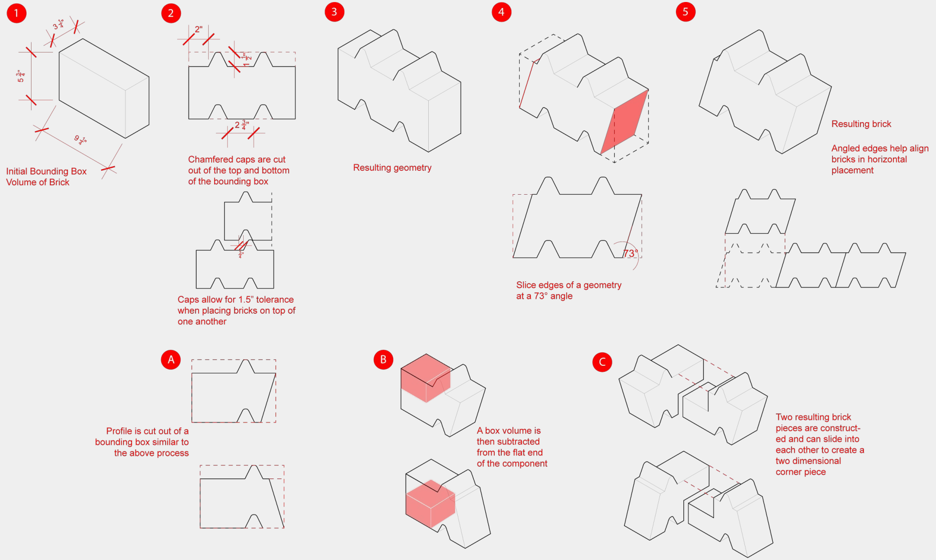
Power
- Motor (2216 KV880)
- Electronic speed control (30w)
- Propeller x 4 (1045)
- Battery (5200mah)

Drone Hardware



Drone Hardware

- F450 frame
- Motor x 4
- Electronic speed control x 4
- Propeller x 4
- Pixhawk 2.4.8
- GPS module
- Vibration damping pad
- Radio controller
- Battery
- Battery charger
- GPS stand
- FS-CVT01 Voltage Collection Module
- Raspberry Pi 4 board
- SD Card



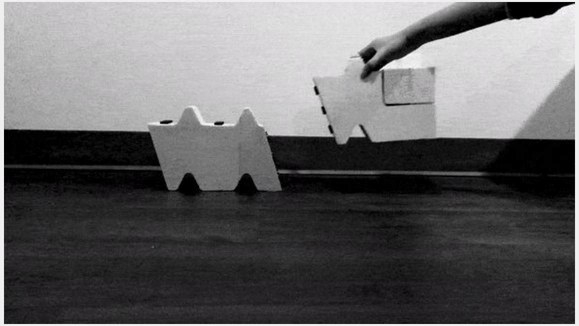
Foam Bricks

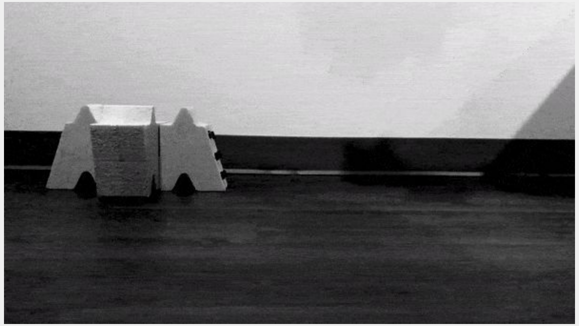
- Design features to compensate for the inaccuracy of drone localization
- Specialized brick components are designed so bricks can adjust themselves into place

Design features:

- Caps are introduced at the top and bottom for vertical alignment
- Slanted edges help bricks slide into place in horizontal alignment

Building Components





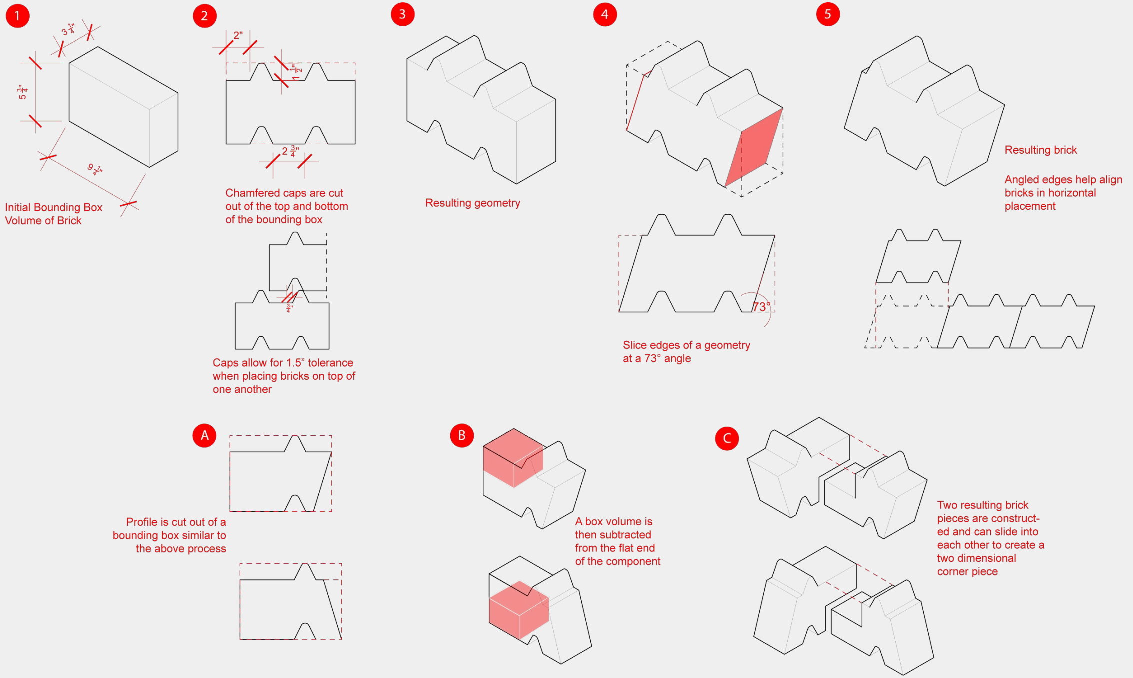
Foam Bricks

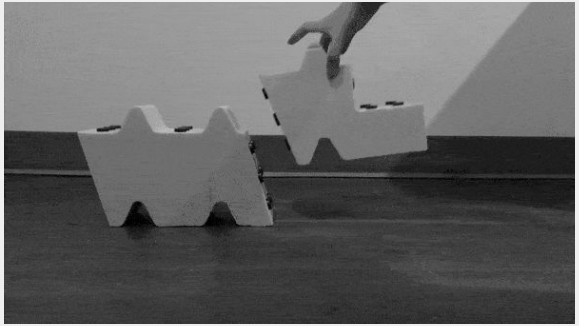
- Design features to compensate for the inaccuracy of drone localization
- Specialized brick components are designed so bricks can adjust themselves into place

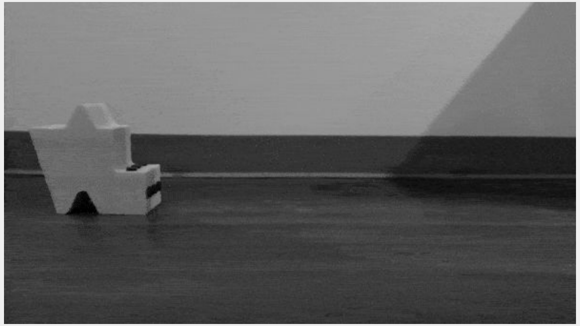
Magnets:

- Multiple magnets are attached onto the brick
- Further help the bricks snap into place in both the x and y directions

Building Components

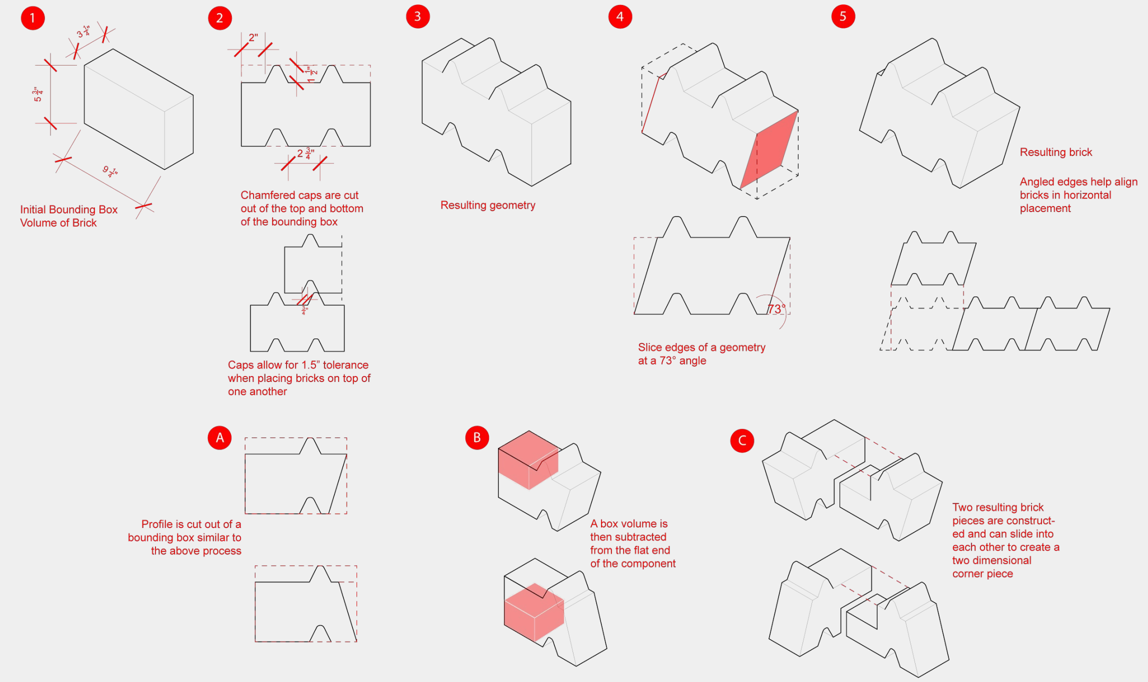


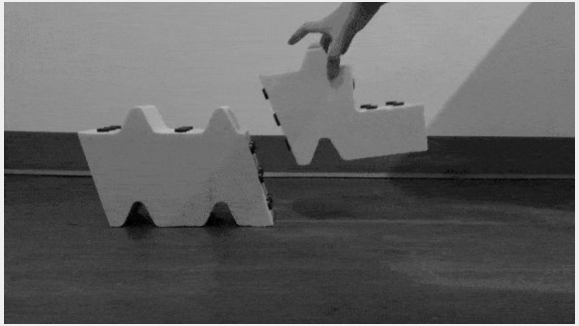


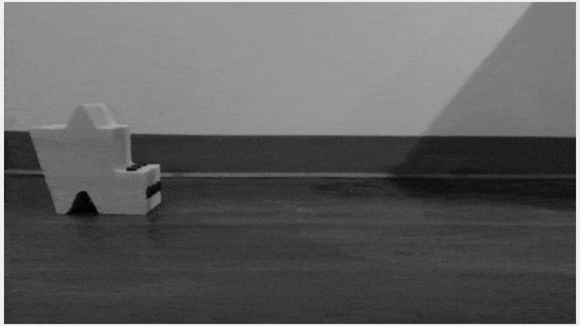


Building Components

- Discrepancies between a drone's simulated versus real position can cause potential misalignments in a pick-and-place procedure
- To account for this, specialized brick components are designed so bricks can adjust themselves into place
  - Caps are introduced at the top and bottom for vertical alignment
  - Slanted edges help bricks slide into place in horizontal alignment







Building Components

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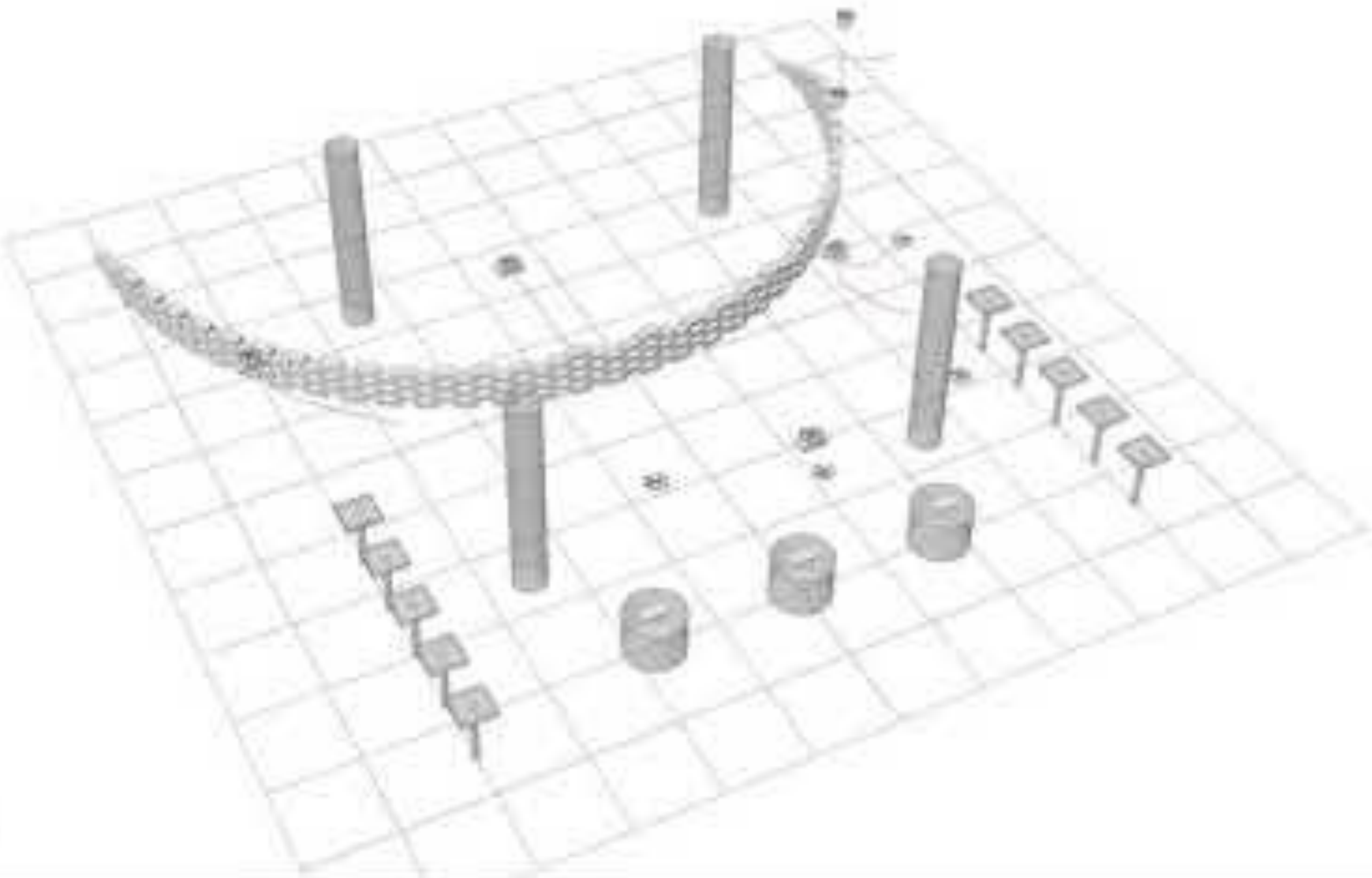
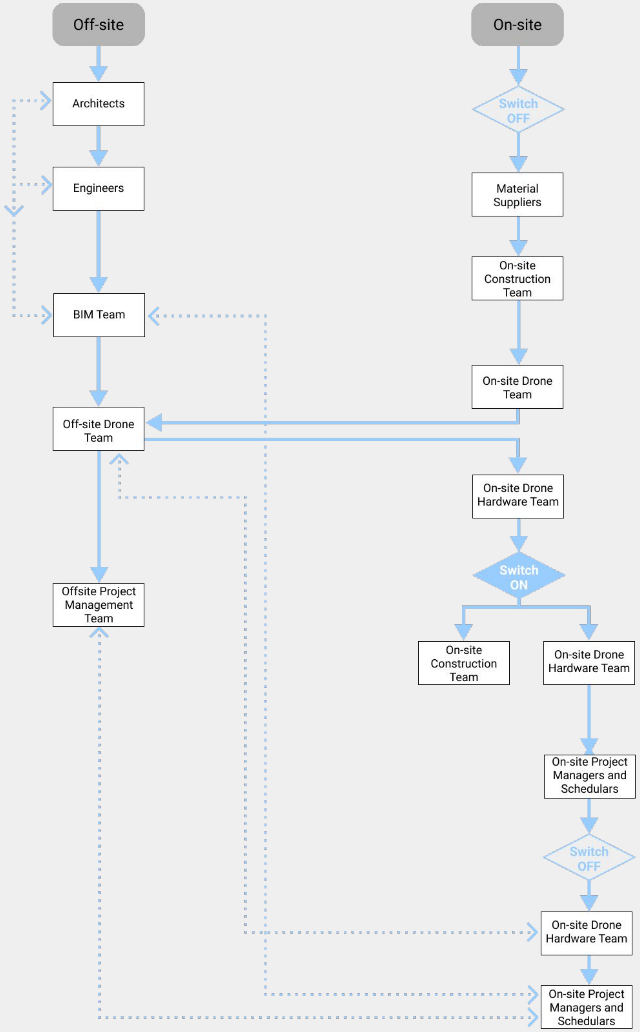
  - Multiple magnets are attached onto the brick
  - These magnets further help the bricks snap into place in both the x and y directions

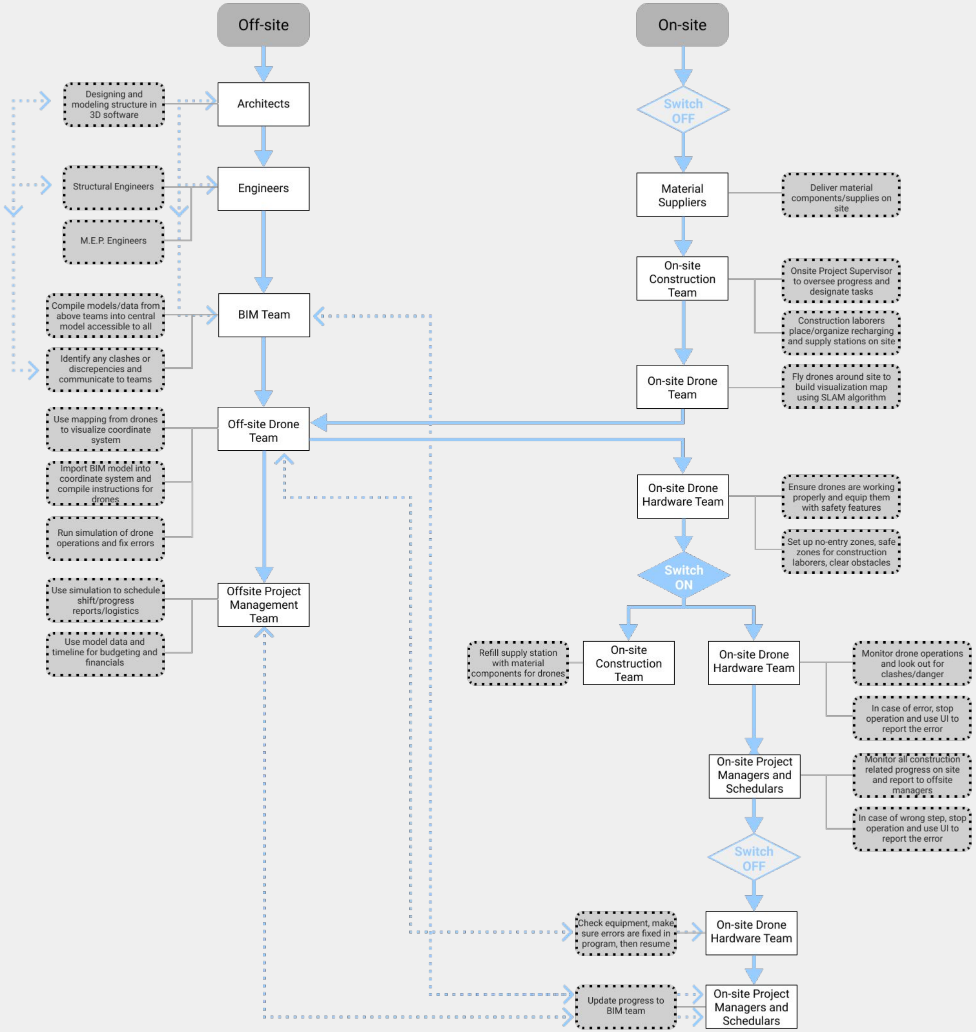


8x Speed



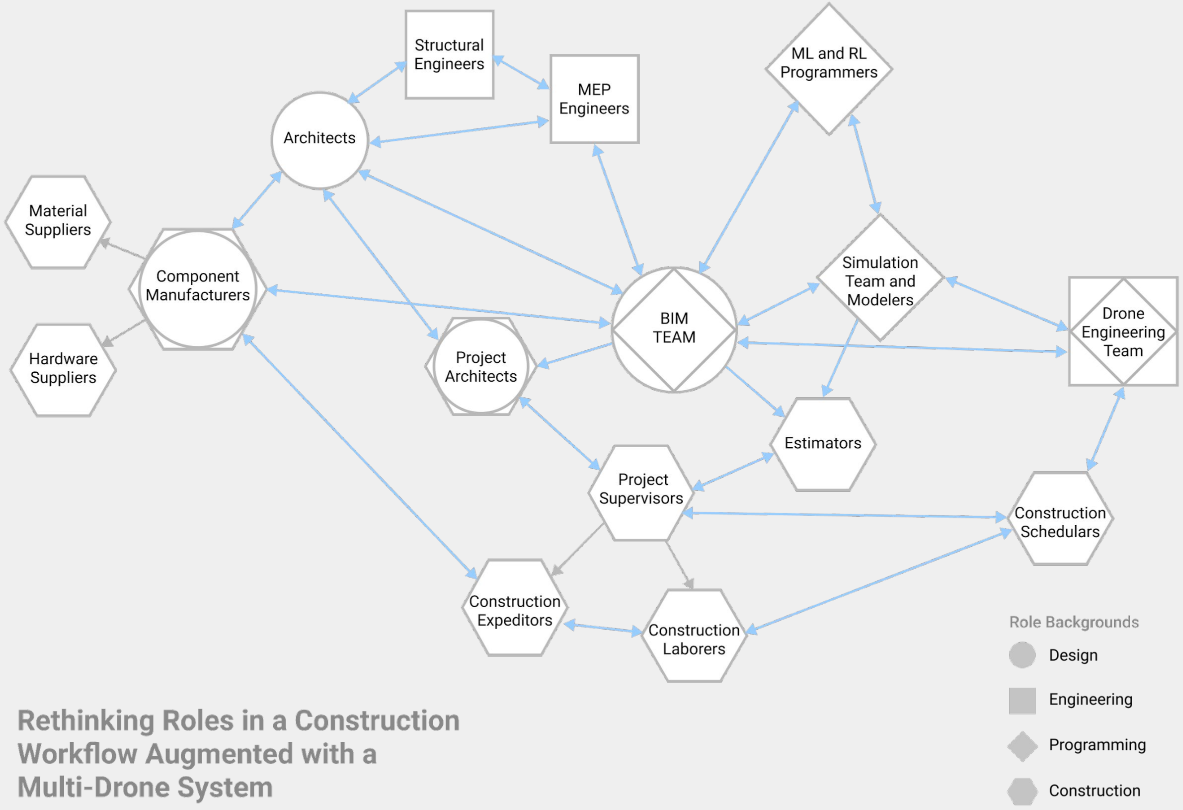
Long-term Project Workflow

- Simplified



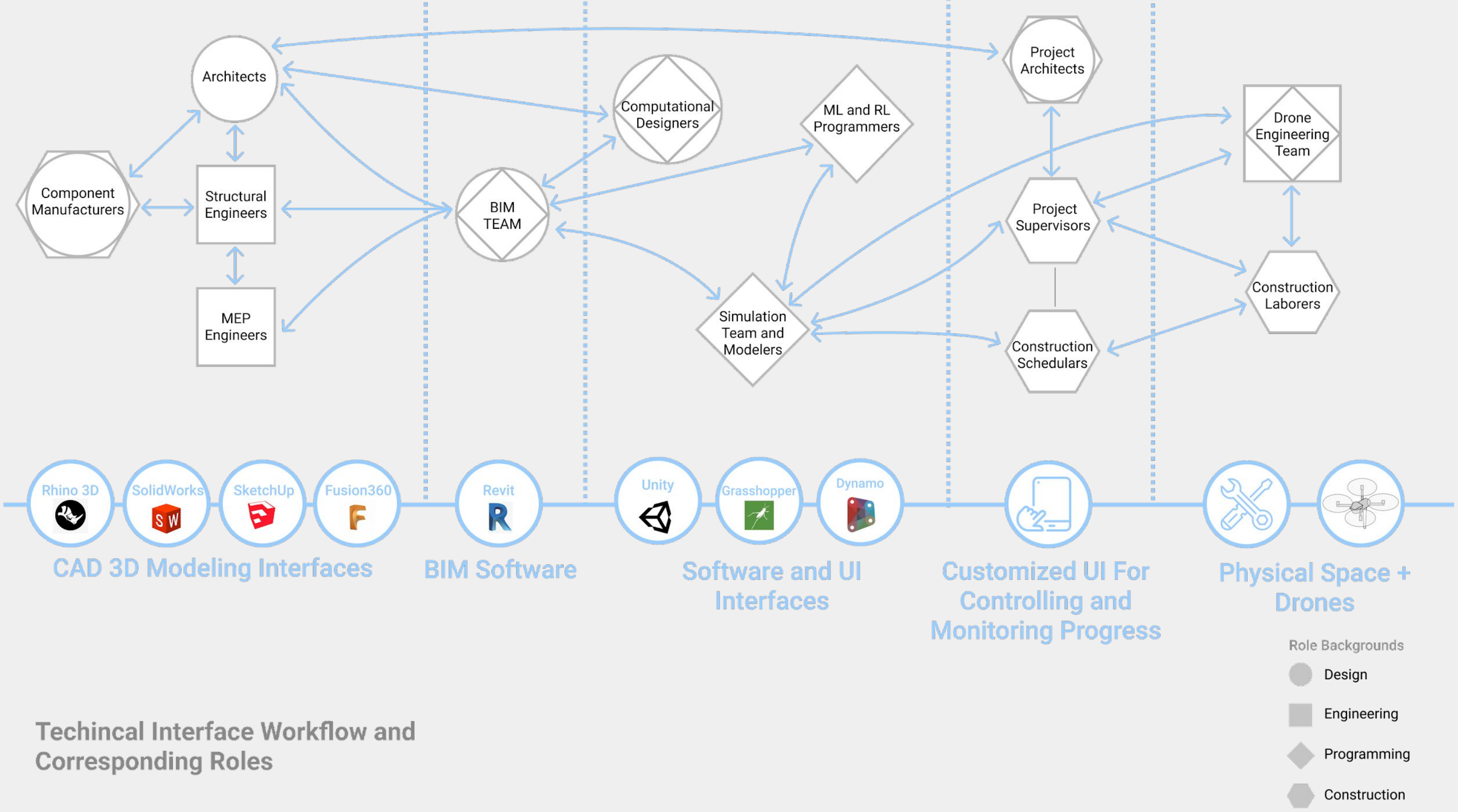
Long-term Project Workflow

- Extended



Rethinking Roles in a Construction Workflow Augmented with a Multi-Drone System

Human Roles in the Framework



Technical Interface and Human Roles

Although the proposed system seems promising for multiple drones to automate construction tasks with improved efficiency, limitations still exist.

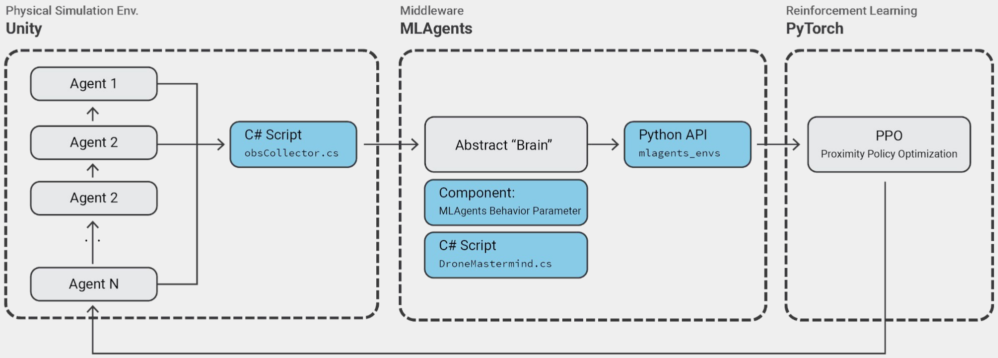
- **Problem formulation limitation** - the problem which is addressed in this use-case scenario is abstracted, but in the real world, any application of this system would include other variables such as inconsistent construction materials, unexpected and external forces, as well as unpredictable events associated with human agents which potentially limit the generalizability of this method

- **Collaboration limitation** - currently drones complete tasks independently, but in real life scenarios, they may need to rely on each other to complete tasks like lifting heavy objects

- **Robustness limitation** - the driving algorithms need to be more robust to address multiple issues such as battery failure or drastic weather conditions

- **Efficiency limitation** - The resource allocation algorithm currently proposed needs to be developed more to properly and efficiently allocate resources when the number of drones involved increases by a wide margin

Limitations



Evolving the Framework

- Pushing the current framework to a more universal platform.
- Integrated pipeline with full-stack real-time simulation in Unity, middleware communication through MLAgents, and library of reinforcement learning models using PyTorch.
- Investigating other algorithms:
  - MADDPG, DDPG, Cen-Q, Cen-V
  -

Building an Array of Drones

Next Steps

Re-thinking Automation in Construction Project

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- **Michael Hasey**
- **Willa Yang**

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Thank you!

Stay safe!

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