Bottom-Up AI-support to Generate Conceptual Designs For Concurrent Engineering Studies with DRL

Jan-Peter Ceglarek, TU Darmstadt

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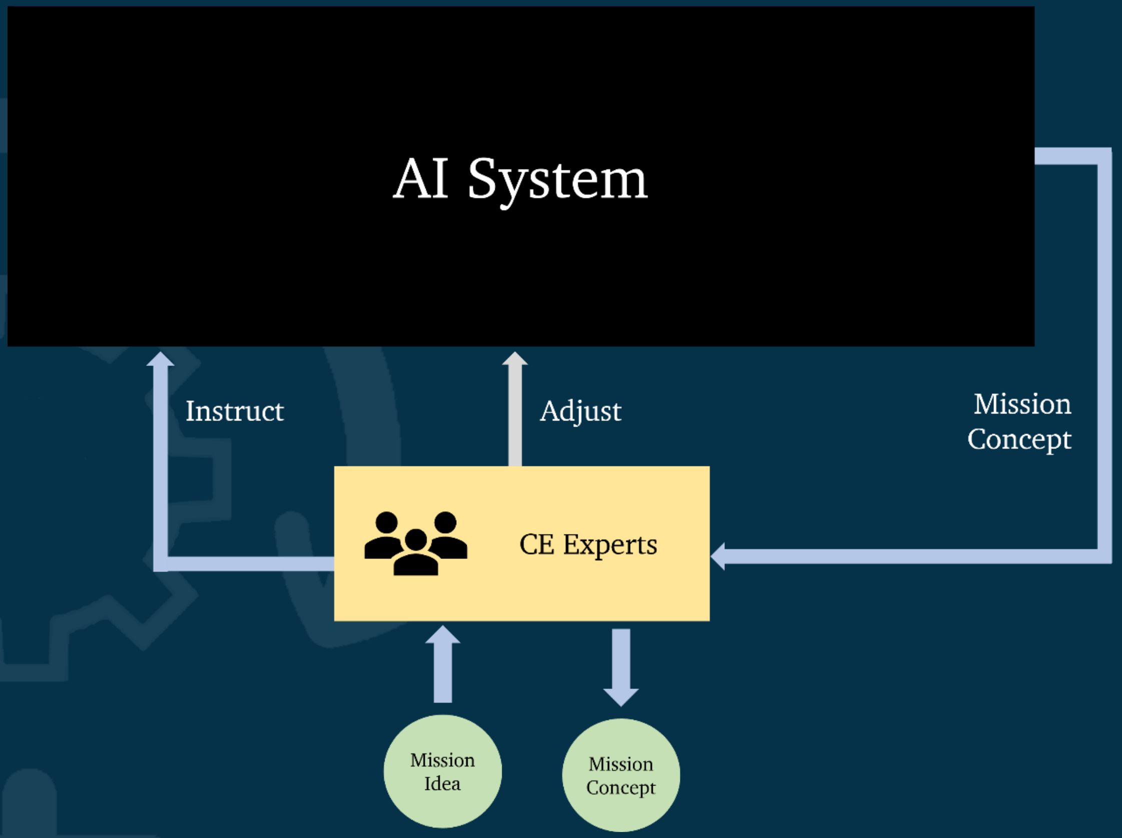
Table of Content

1. Motivation
2. Technical Background
3. Implementation
4. Validation
5. Outlook
6. Summary



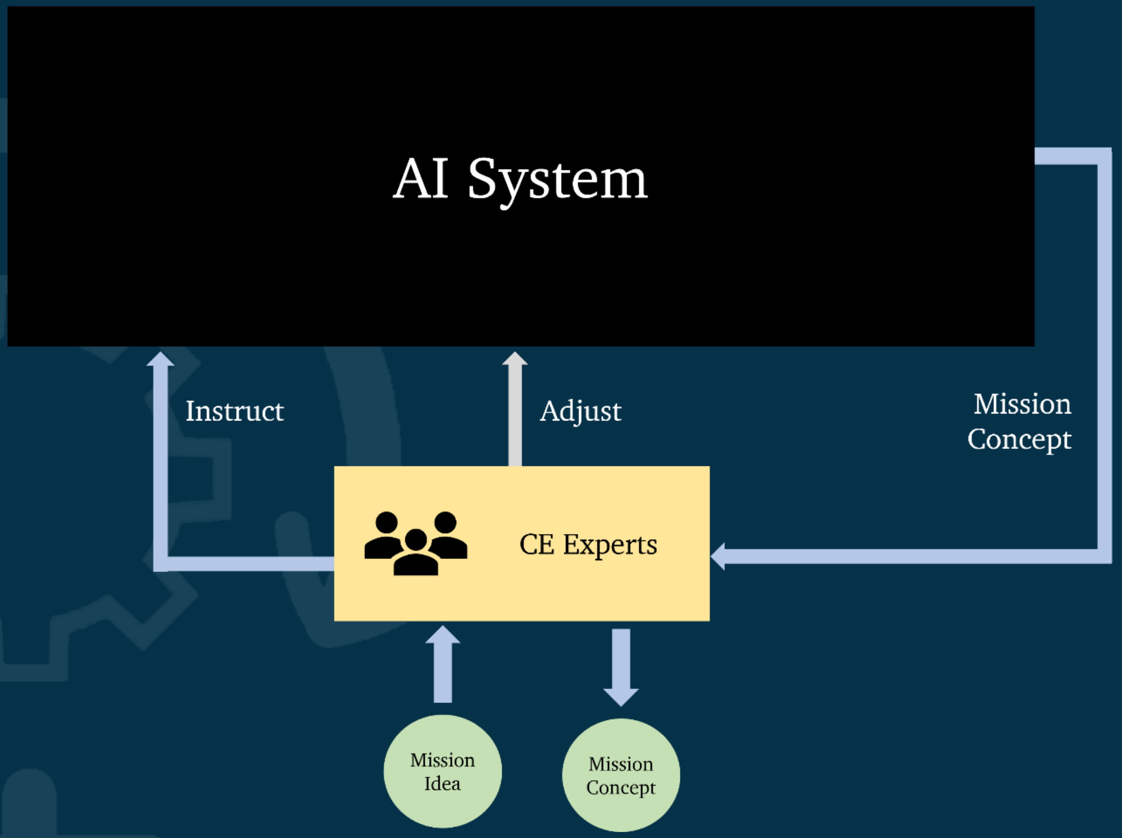
Motivation

Concurrent Engineering

- Unique space missions
- Innovative ideas needed
- Discover possible COTS solutions

Machine Learning Advancements

- Handling large data sets
- Instantaneous trained models
- Deep Reinforcement Learning
- Calculation-based creation



→ Integrated Concept Creation

COTS = commercial off the shelve

Thesis Overview

Goal of the thesis

- Develop system
- Test feasibility and limitations
- Outline prospect for generalisation

Steps to be taken

- Scrape SatSearch.co for components
- Design & implement the AI system
- Validate created CubeSat designs

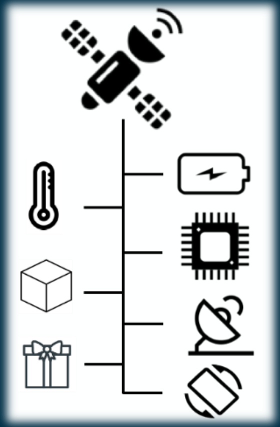
Background

Concurrent Engineering CE

- Creating unique designs
- Formalised process
    - Implementation trade-offs
    - Decisions based on calculations

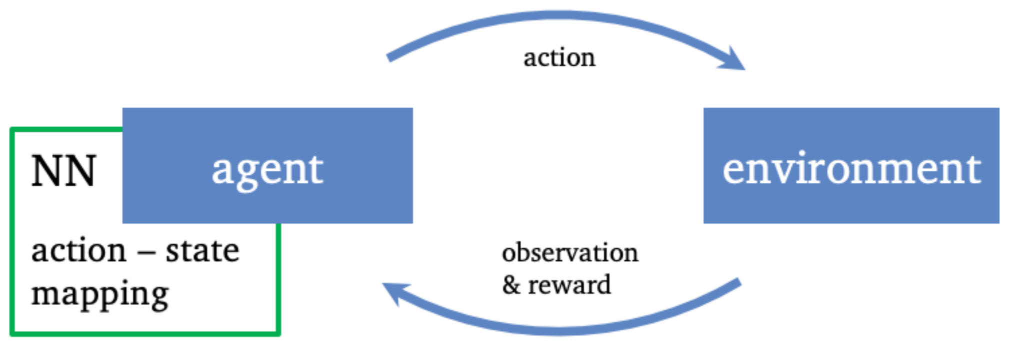
CubeSats

- Low complexity
- Standardized, inter-changeable components
- COTS parts

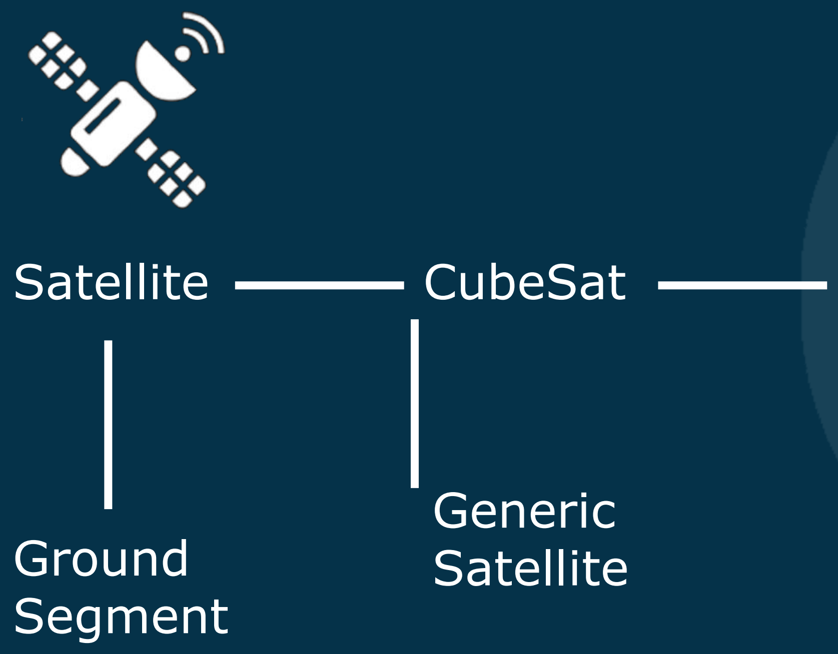


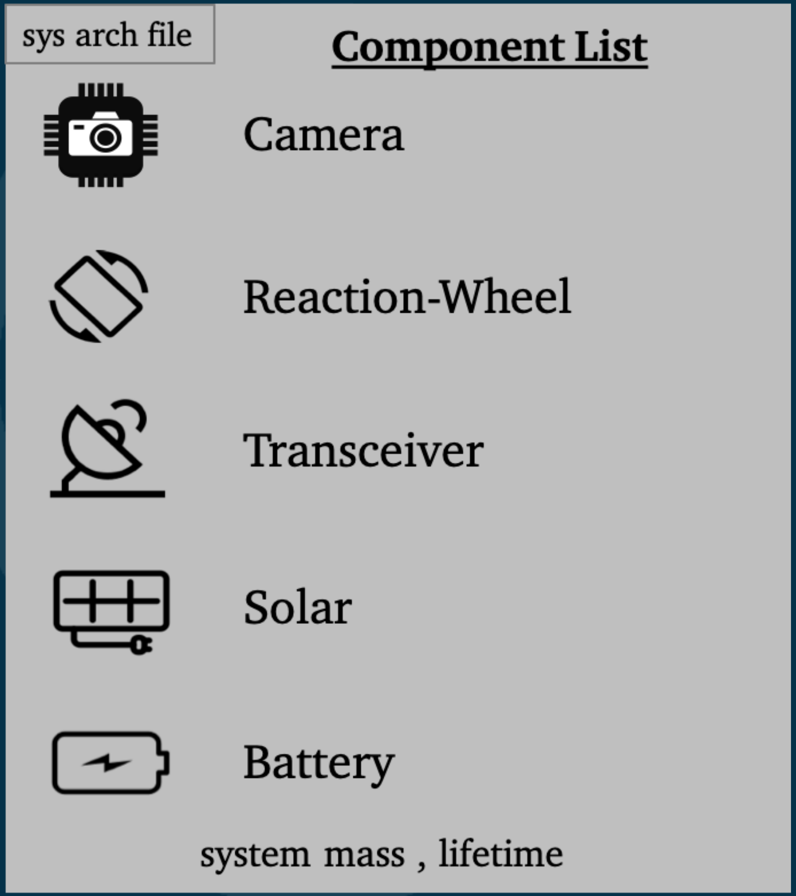
Deep Reinforcement Learning DRL

- Learning by experience
- Rule/calculation-based
- State-Action-Pair
- Neural Network
- Good with discrete design spaces



System Architecture

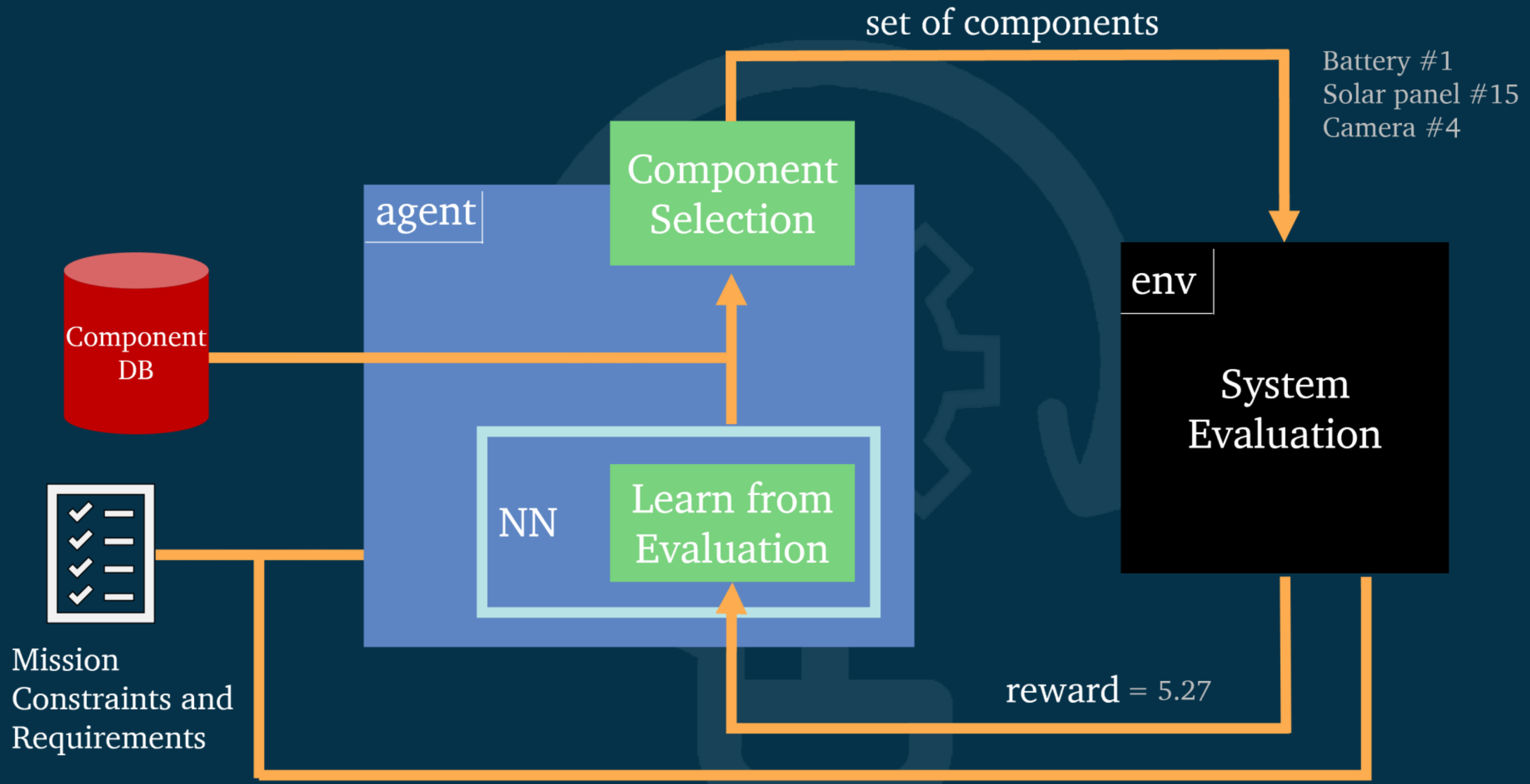




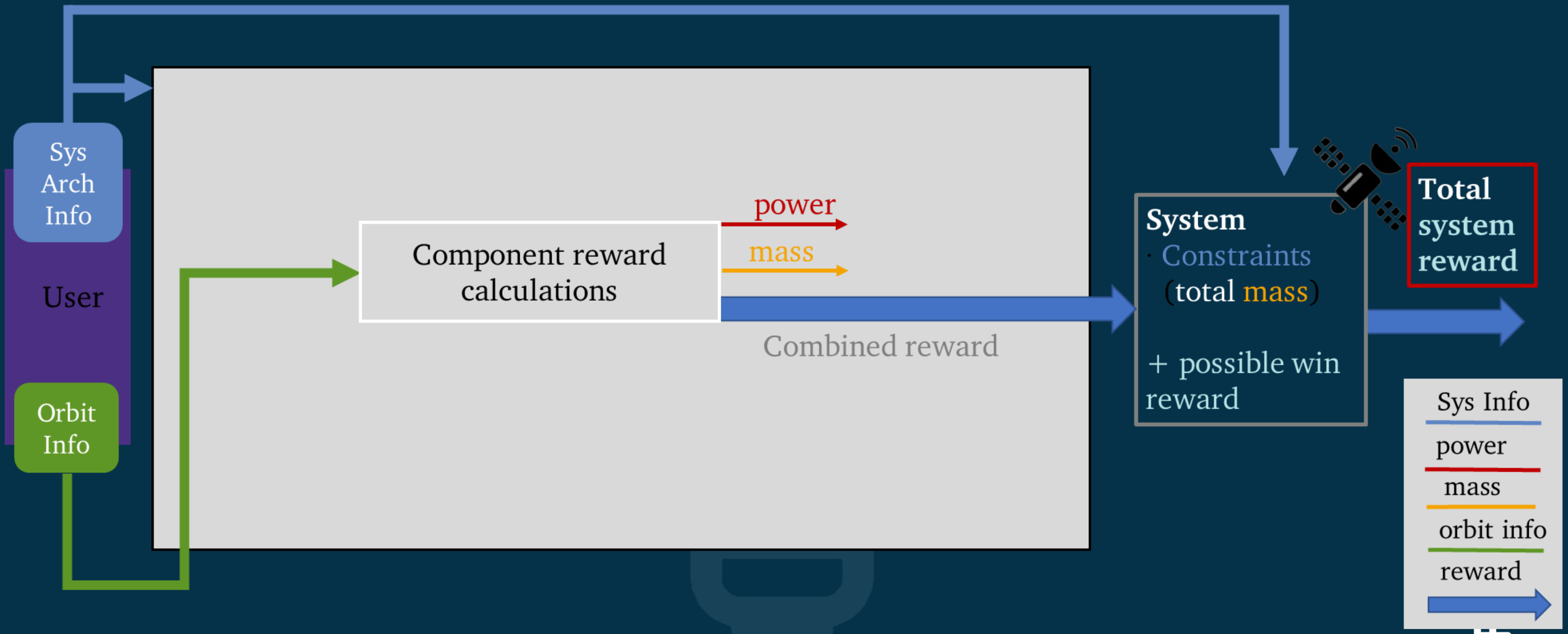
Sys Arch File Extract


```json
{
    "specs": {
        "aocs": {
            "reactionwheel": 0
        },
        "eps": {
            "solar-panels": 1,
            "battery": 2
        }
    },
    "constraints": {
        "mass_total_max": 1000,
        "mass_margin": 0.1
    }
}
```

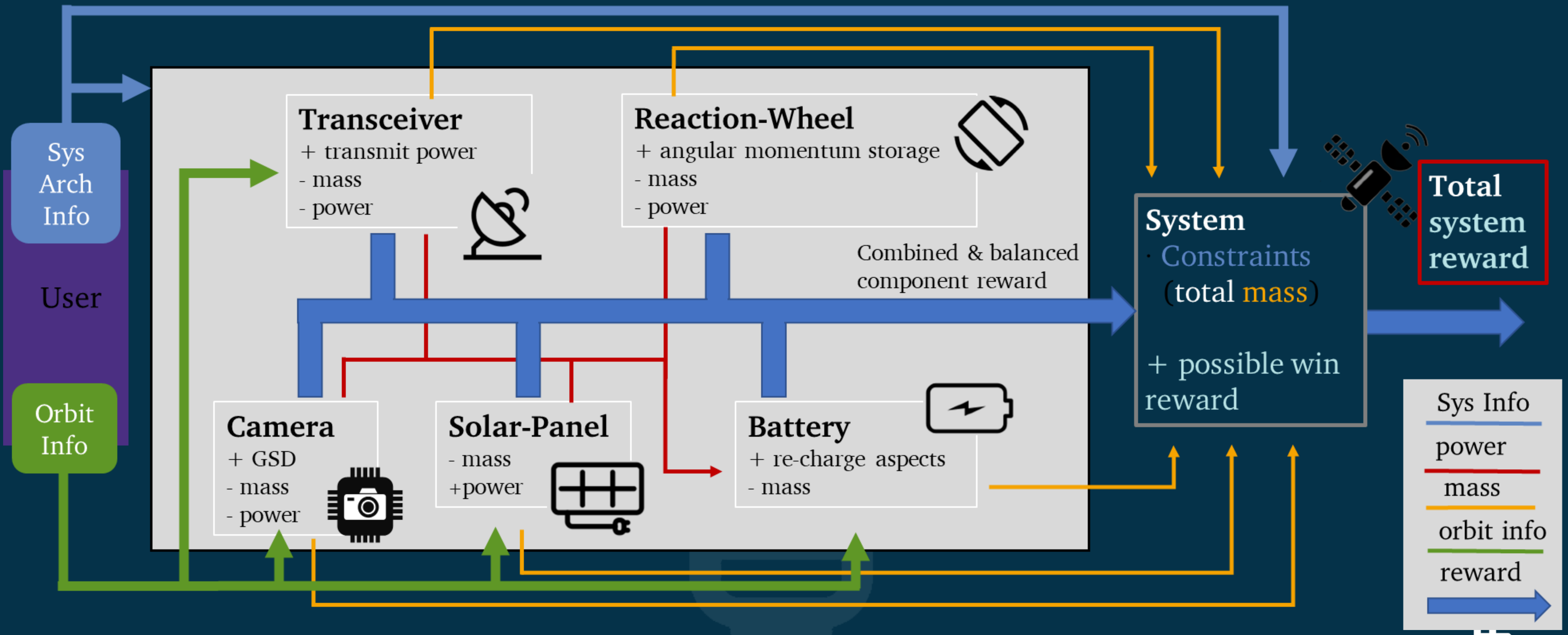
System Architecture



DRL Overview

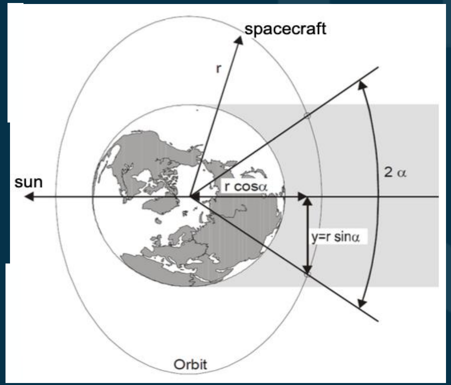


DRL Overview



Reward Calculation Example: Solar Panel

- Mass
- Peak generated Power
- $P_{generated} = t_{sun} \cdot P_{generated,\ peak}$
- Balancing factor

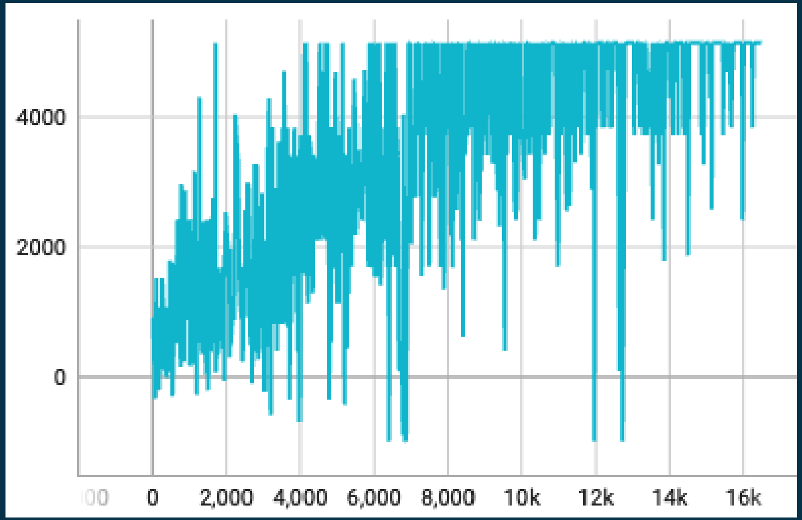


$$\frac{balancing\ factor * \ Pgenerated[W]}{mass[g]} = reward$$

Training Review

1 component system
reaction wheel

System Reward

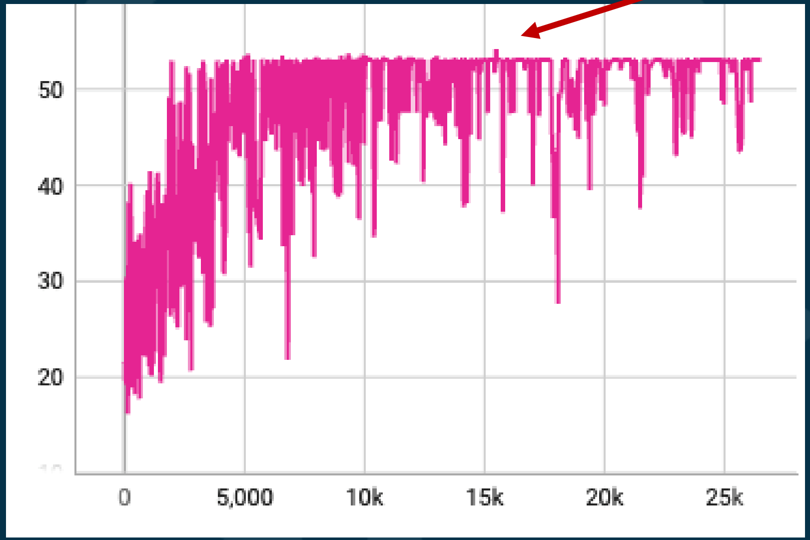


Learning iterations

3 component system
battery, solar panel, transceiver

System Reward

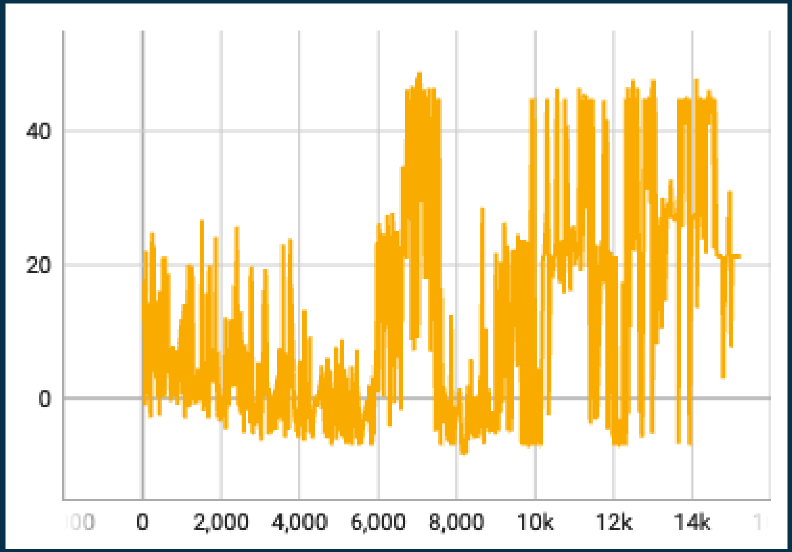
Learning not optimal



Learning iterations

5 component system
battery, solar panel, transceiver, reaction wheel, camera

System Reward



Learning iterations

→ **Complex designs getting less stable training**

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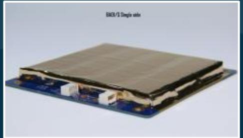
5 Component Result

```
$ python dcc.py
________________________________________
The trained model selected the following component as the best option available:
Name: 25 Whr High Energy Density LiPo Battery Array
ID: 2270179
Link: https://satsearch.co/products/exa-25-whr-high-energy-density-li-po-battery-array
Specs: ______________
mass : 125 g
width : 95 mm
length : 89 mm
height : 7 mm
battery pack power : 22.2 Wh
battery type : Li-poly
battery pack voltage : 3.7 V
battery capacity : 6000 mAh
```

Battery



125 g
22.2 Wh

Solar Panel

570 g
+19.2 W

System
mass = 1.2 kg
$P_{balance}$ = 10.8W

Transceiver

72 g
3.1 W

Reaction Wheel

21 g
0.8 W

Camera

400 g
4.5 W

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Validation

What was to be tested?

1. **Applicable** component choice
   - Valid CubeSat?

2. **Optimal** component selection
   - Best possible component selection?

3. **Robustness** of the trained model
   - Trained model in new scenarios
     - Same components
     - Different orbit & mass

How was it tested?

Within design space

1. **Tests with increasing system size**
   - 1 ..5 component
     - AI creation
     - Combinatorics

2. **Altered design constraints**
   - 10kg @ OPS-Sat , ISS , GEO
   - 10,000 kg @ OPS-Sat , ISS , GEO

Reality

3. **Comparison with real world missions**

   ! Different component databases
   - **3U** OPS-Sat , UPSat , BOBCat-1
   - **1U** EQUiSat

Validation Result Examples

Test1: 1 .. 5 components

- Concept generation possible
- More complex systems are less stable

Test2: 10,000 kg @ GEO

transceiver, solar panel, battery

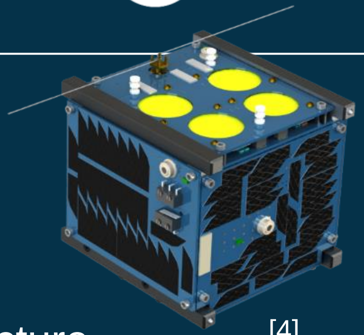
AI tool	Combinatorics
1U solar panel	3U solar panel
mass = 221 g	mass = 4135 g
$P_{balance}$=- 0.8 W	$P_{balance}$= 4.9 W

- CubeSat, although different constraints
- Constraints not exhausted
- Model not very robust
- Not a problem of the trained model

1U=best case

trained scenario:
10kg @ OPS-Sat orbit
transceiver, solar panel, battery

EQUiSat



[4]

transceiver, solar panels

Batteries + payload + structure

AI tool	EQUiSat
1U solar panel	1U solar panel
mass = 800 g	mass = 1350 g
$P_{balance}$=- 2.3 W	$P_{balance}$= -5 W

$mass_{system}$	- 32 %
$P_{balance}$	- 54 %

→ Fitting within limitations
- Missing components
- Different database

Outlook

Usage in CE

- AI assistant during sessions
- Unbiased design creation
- Current design with COTS parts

Education

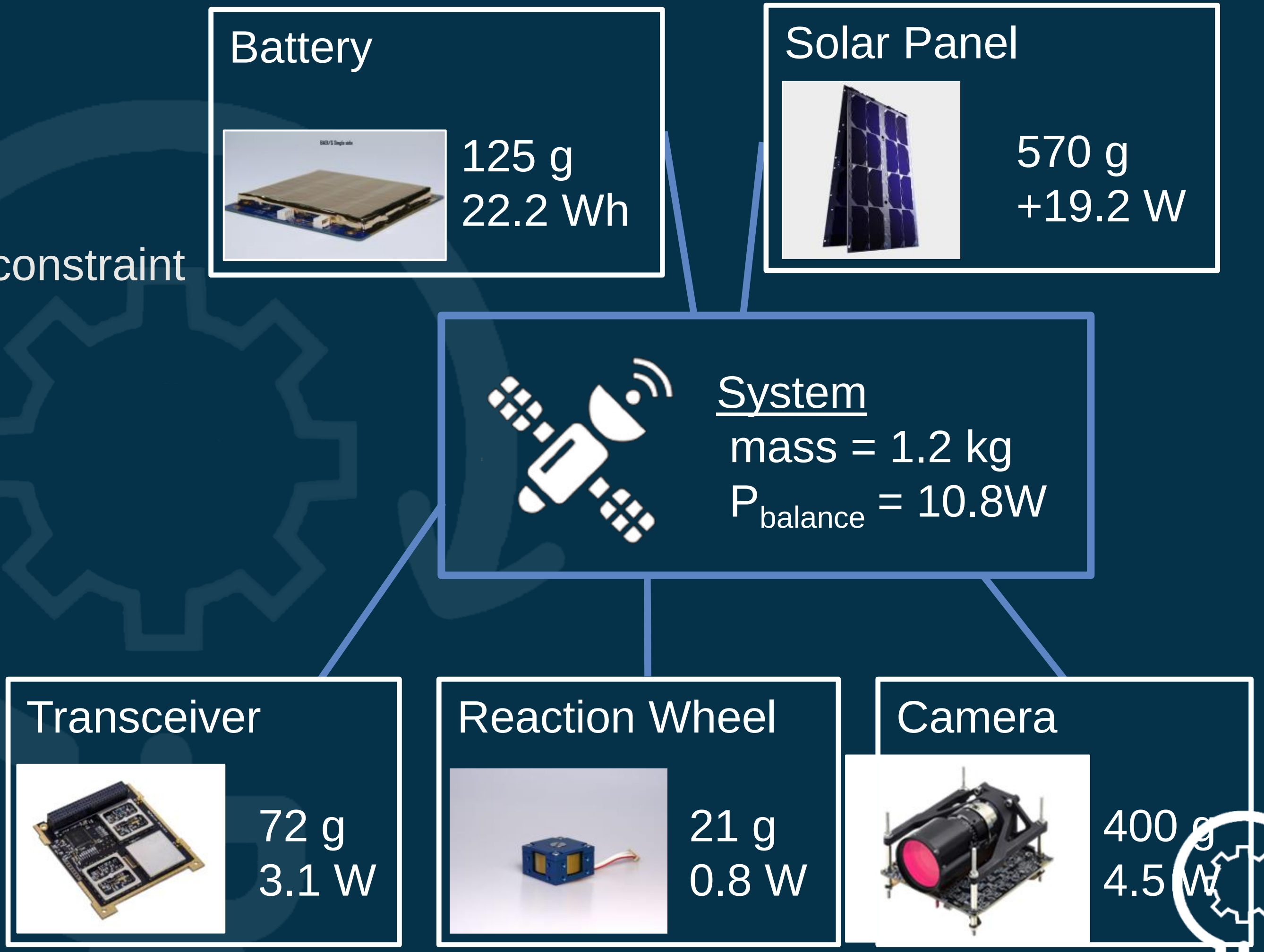
- Concepts as an *Option* in COMET
- COMET's *Model Catalogue* as database

Generalisation

- Other satellites
  - Possible with small reward adjustments
- Others: Ground Segment …
  - Component-based architecture
  - Reward functions needed
  - Component database
  - Exchangeable components enabled by fixed interfaces

Summary of Thesis

1. Development of AI concept creation tool
2. CubeSats can be created with DRL
   - Best for small CubeSats
   - Future improvements for exhausting constraint
3. Tool as a framework for concept creation
   - Scalable design
   - Designed with other systems in mind
   - Future studies with other systems



Agree/Disagree Questions

1. Should AI methods be used for CE support?
2. Could Deep Reinforcement Learning be a suitable candidate for that?
3. Would a representation of a system design as an MBSE model be a good idea?

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